Trump Tweets and Stock Markets: Analyzing Sentiment Influence on S&P 500 Companies

By Vaughn Hajra

This research project investigates President Donald Trump's tweets' influence on publicly traded companies' stock market performance. Utilizing data encompassing Trump's entire presidential term and employing sentiment analysis, I analyze the extent to which the sentiment of his tweets correlates with stock market outcomes. The study finds a significant positive cumulative average abnormal return (CAAR) following positive tweets and a significant negative CAAR after negative tweets were made, with some variation by reach and market sector.

I. Background

The intersection of social media and financial markets has garnered substantial attention in recent years (Yasseri, 2016). Twitter and other social media platforms have increased the speed and breadth at which information spreads (Mitchell, 2021). In the financial world, where news and sentiment often drive market dynamics, social media's impact has become a focal point of investigation. This study investigates the connection between social media and financial markets, specifically exploring the influence of President Donald Trump's Twitter sentiment on stock market performance.

In this analysis I utilize an events study framework to analyze Trump's tweets. First, I find that regardless of sentiment, positive abnormal stock returns are observed after a tweet is made. Furthermore, when dividing tweets by sentiment, abnormal returns follow what one would intuitively expect: positive tweets with positive returns and negative tweets with negative returns. Finally, different market sectors are examined, revealing varied outcomes for significant abnormal returns by sector. These findings show the importance of an investigation into the social media activity of major political figures, and President Trump remains a great starting point.

The ubiquity of President Trump's Twitter activity during his tenure in office underscores the potential significance of his tweets in influencing the behavior of financial markets. As the 45th President of the United States, his tweets have the power to affect public perception (Christenson, 2021) and, by extension, the valuation of publicly traded companies. Evaluating how the sentiment of President Trump's tweets affects stock market performance is crucial.

The research questions at the heart of this study are threefold: To what extent did the sentiment of President Donald Trump's tweets mentioning publicly traded companies correlate with those companies' subsequent stock market performance? And, how does the specific sentiment value for positive and negative tweets relate to stock outcomes? Finally, do the previous findings hold when considering specific market sectors and the reach of tweets?

Previous research has assessed the impact of President Trump's tweets on stock market performance, yielding a spectrum of findings. Brans and Scholtens (2020) found that President Trump's tweets did not yield a significant market response regardless of sentiment. However, when considering negative sentiment, they detected a discernible impact on the stock prices of affected companies. On the other hand, Juma'h and Alnsour (2018) reported no significant effect of President Trump's tweets on the market. Multiple other studies have also found conflicting results with slightly different research designs. While these studies have shed light on the relationship between tweets and market performance, there remains room for more examination.

This study aims to extend the existing body of research in the following ways: First, where prior studies used data only through 2019, I expand the sample by considering all tweets made during President Trump's entire time on the campaign trail and in office. By expanding the dataset to encompass the entirety of his campaign and presidency, this research aims to provide a thorough understanding of the impact of his tweets over the full course of his presidency.

Furthermore, this study introduces a novel approach by introducing subsets and controls not previously considered. First, the influence of tweets may not be uniform across different market sectors, so I include sector-specific subsets to address this. Additionally, the reach of the tweets, approximated by the number of retweets, is introduced as another control - you would expect tweets with more reach to have a more profound impact on markets.

By considering multiple sentiment databases, market sector effects, and tweet reach, this research aims to provide a richer and more comprehensive understanding of how President Trump’s tweets affect stock performance.

In the next section I will discuss the theoretical reasoning for why a tweet may have the ability to impact stock prices and valuation. Section III details the data I use for this project, and also provides a background on the sentiment libraries. Section IV describes the empirical approach that I use, followed by the results in section V. Section VI offers potential improvements and starting points for future research, and Section VII gives final conclusions.

II. Theoretical Reasoning

President Trump was arguably the first U.S. president to fully embrace Twitter, an approach that had both positive and negative ramifications (Minot, 2021). On the positive side, this form of communication gave the general public unprecedented access to a sitting president's opinions and insights. The immediacy of Twitter allowed for real-time updates on the president's views, which, in turn, offered a wealth of information and insider access to the highest office in the nation. However, this openness also came with potential drawbacks. Foreign countries could gain insights into the U.S. economy that might not be suitable, potentially putting the entire nation at risk (Mazetti, 2022). Some of President Trump's tweets were viewed as unfiltered and even childishly provocative (Burke, 2019), raising questions about the appropriateness of such a platform for the leader of the free world.

In this newfound landscape, publicly traded companies were in an unprecedented situation. For the first time in history, companies were subject to real-time feedback from the President of the United States (Ballhaus, 2017). President Trump, with his unique position and access to information, had the potential to offer insights into companies that were not previously available. This dynamic was not merely a matter of increased transparency but also a potential influence on market behavior.

From a financial perspective, there are multiple explanations for a change in current stock valuation or stock prices. To explain these potentials, I will use the Gordon Growth Model, originally developed by Myron Gordon published in the Review of Economics and Statistics in 1959. Assumptions of the Gordon Growth Model are that the company's business model is stable, there is a constant growth rate, the company has stable financial leverage, and the company's free cash flow is paid as dividends. Although there are limitations to the model due to these assumptions, it can be utilized to explain the theoretical framework for why a Trump tweet may affect a company's stock. The model specification is as follows:

$$V_0 = \frac{D_1}{R-g}$$

Where V_0 is the present valuation of a stock, D_1 is the expected dividend in the next period, R is the required rate of return and g is the expected dividend growth rate. The first possible explanation for a tweet having an effect on stock price is if Trump's supporters liked him enough that they were willing to accept lower rates of return to invest in a stock because he endorsed it. Furthermore, there would have to be enough people willing to accept a lower rate of return to affect market prices, which would be associated with positive abnormal returns. This is a rather unlikely scenario, but Trump's supporters while he was in office were both vocal and numerous. There is a possibility that Trump had enough sway to convince investors to accept a lower rate of return, simply because he praised the company.

Two more possibilities, that I am much more likely to accept, are that Trump either affected companies' cash flow (D_1) or revealed better information related to companies' growth rates (g). By tweeting about a company, Trump could cause consumers to purchase that company's products increasing sales and therefore increasing the expected cash flow. This would cause an increase in the stock's valuation while leaving the growth rate unchanged. A graph of this idea is shown in Figure 1.

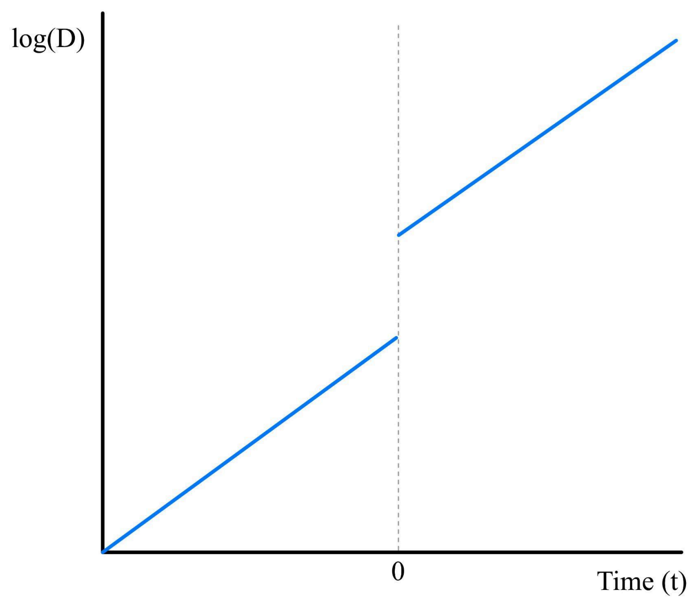


Figure 1. Increase in Expected Cash Flow.

Log of the dividend (D) on the y-axis and time before and after the tweet is made on the x-axis, with 0 indicating the date that the tweet was made. Note that there is a one-time increase in dividend, and the dividend growth rate (g) remains constant.

The final potential explanation for an increase in stock valuation is if Trump, with his unique access to information, reveals new information in his tweets related to companies' growth rates. Rather than a one-time change in cash flow, this would instead be a change in the rate at which dividends are earned. According to the Gordon Growth Model, which assumes growth rates are unchanging, this change in growth rate would also increase the stock's valuation. An example of this is shown in Figure 2.

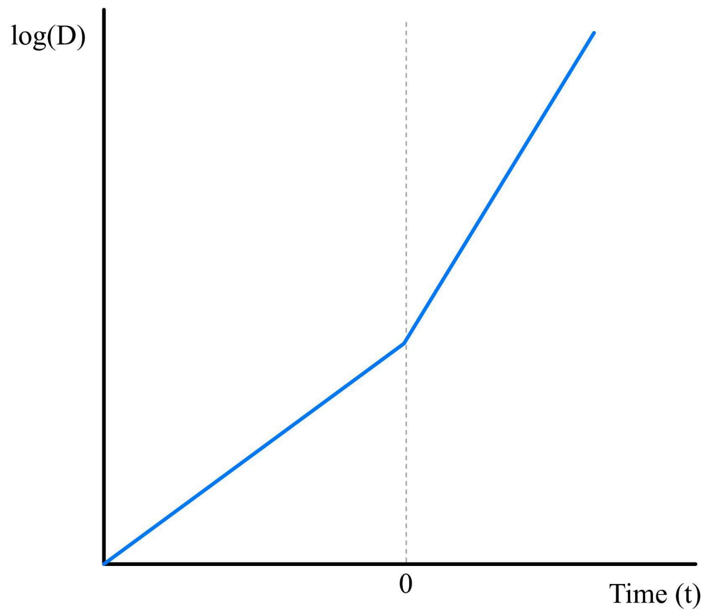


Figure 2. Increase in Growth Rate.

Log of the dividend (D) on the y-axis and time before and after the tweet is made on the x-axis, with 0 indicating the date that the tweet was made. Note that the increase in growth rate causes a change in the rate of dividends earned rather than a one-time increase in Dividends.

The importance of this study also relates to government figures' social media accounts and the potential need for regulation. There is a fine line between regulation and censorship, and by no means am I suggesting controlling what our leaders can and cannot say. However, an interesting question arises if politicians can manipulate markets: Should there be oversight related to social media and potential market manipulation by major politicians?

(this space is purposely left blank for ease of reading)

III. Data & Descriptive Statistics

Data Collection and Preprocessing

I obtained President Donald J. Trump's tweets from the Trump Twitter Archive (the tweets were also made accessible via Google Sheets for future replication). To facilitate cross-referencing with stock market data, I standardized each tweet by converting all characters to lowercase and removing special characters. The names of S&P 500 companies underwent a similar preprocessing step, in which the company names were converted to their "common name" (for example, *google* instead of *alphabet*). Custom functions were applied to identify specific companies in the tweets to capture as many possible tweets as possible. Then, I completed a manual check to filter out the excess tweets that did not mention a company.

I acquired historical stock prices for S&P 500 companies using Google Finance data. This process involved using Google Sheets to query data for each event on a specific date in the event window and the estimation window, resulting in over 30,000 queries for the negative subset alone. I then exported the dataset for subsequent analysis in Stata

General Sample Statistics

Following the initial data cleaning process, the dataset consisted of 511 unique events. Subsequently, I narrowed the dataset to encompass only tweets posted after President Trump declared his candidacy in June 2015, resulting in a sample of 311 events.

Within this subset of 311 events, Trump mentioned 33 distinct companies. The top two most frequently mentioned companies were Graham Holdings Co., the parent company of the Washington Post, with 77 mentions, and CBS' parent company, Paramount, with 60 mentions. Trump mentioned Google 33 times, Amazon 23 times, and Apple 20 times. All other companies garnered 15 or fewer mentions, representing various market sectors.

Among the tweets, Trump referenced seven different market sectors. Consumer discretionary is the most frequently mentioned sector, with 214 references, followed by information technology (56 mentions) and the industrial sector (19 mentions). Energy, financials, healthcare, and telecommunications services received fewer than ten mentions each.

Sentiment Scores and Classification

I performed sentiment analysis in this study using the Bing and Afinn databases. Bing provided binary positive/negative scores for each word, while Afinn provided positive/negative scores with magnitude. The sentiment analysis function created for this study parsed the tweets word by word and created an aggregated sentiment score for each tweet. This analysis aimed to gauge the overall sentiment of a tweet.

For example, the following tweet is classified as negative by both the Bing and Afinn sentiment libraries:

This sample tweet is classified as positive by both the Bing and Afinn sentiment libraries:

Tweets were then classified into three main categories: positive, negative, or neutral, based on the assessments provided by these two libraries. To classify a tweet as positive, I considered two conditions: first, if both sentiment analysis libraries agreed in assigning a positive sentiment label; second, if one library indicated a positive sentiment while the other rated it as neutral. This dual-criteria approach ensures a comprehensive capture of positive sentiments, accounting for potential variations in the libraries' lexicon and semantic analysis. Consequently, a total of 119 tweets are positive.

Similarly, the classification of tweets as negative followed a parallel methodology. I classify a tweet as negative if both sentiment analysis libraries agreed on its negative sentiment or if one library identified it as negative while the other deemed it neutral. This approach resulted in a total of 197 negative tweets. Additionally, tweets were classified as neutral if both libraries jointly assigned this label. A total of 39 tweets in the sample have a neutral emotional tone.

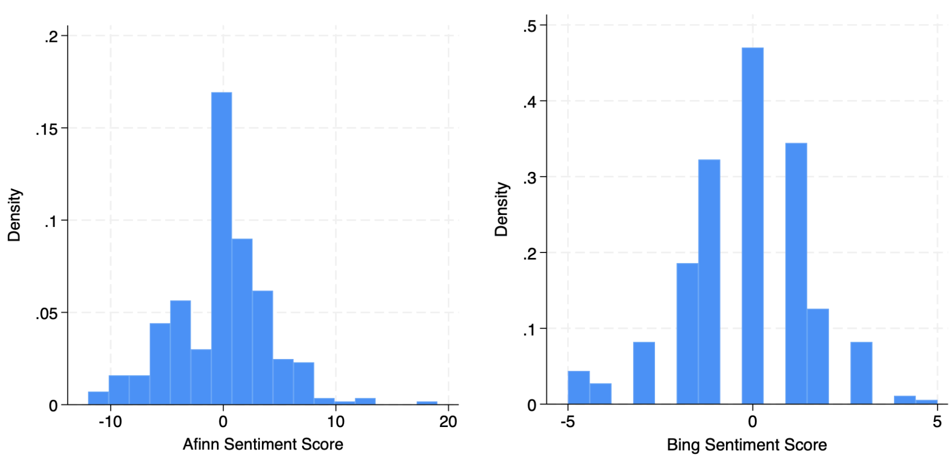
Lastly, when the sentiment analysis libraries offered conflicting assessments, categorizing a tweet as positive or negative became challenging. In such cases, the tweets were labeled "conflicting," shedding light on instances where the sentiment analysis libraries did not concur. A total of 19 tweets fell into this category, indicating potential areas of ambiguity and complexity in the emotional expressions found in tweets.

		Afinn Sentiment Library			
		positive	neutral	negative	total
Bing Sentiment Library	positive	85	13	6	104
	neutral	21	39	26	86
	negative	13	11	97	121
	total	119	63	129	311

Table 1. Tweet Classification by Sentiment Library. *This table illustrates sentiment classification using the Bing and Afinn sentiment libraries. A total of 311 tweets were assessed.*

The distribution of the overall sentiment scores, as evaluated by both the Afinn and Bing sentiment libraries, exhibits characteristics consistent with normality, featuring mean values of roughly zero (Figures 3 & 4). However, distinct disparities emerge in the standard deviations of these distributions. The Afinn sentiment scores display a broader distribution with a standard deviation of approximately 4, reflecting the library's capacity to assign both magnitude and sentiment values (ranging from -3 to +3) for individual words.

In contrast, the Bing sentiment scores exhibit a narrower spread with a standard deviation of roughly 1.75, consistent with its binary approach of assigning -1 or +1 for each word. This variance in standard deviations aligns with the inherent differences in granularity between the two libraries, as Afinn provides a more in-depth assessment and Bing employs a straightforward approach.



Figures 3 & 4. Tweet Classification by Sentiment Library. *Distribution of sentiment scores for each sentiment library. Each histogram includes all 311 tweets in the sample.*

Sentiment by Market Sector

		Bing		Afinn	
Market Sector	Observations	Mean	SD	Mean	SD
Consumer Discretionary	214	-0.47	1.73	-0.93	4.11
Energy	7	1.00	0.58	1.71	1.25
Financials	3	-0.33	2.31	1.00	6.00
Health Care	9	0.00	1.22	0.78	1.79
Industrials	19	1.95	1.31	4.68	4.69
Information Technology	56	-0.09	1.55	0.54	3.77
Telecommunications	3	-0.67	0.58	-1.33	1.15

Table 2. Sentiment Summary Statistics by Market Sector. *This table illustrates sentiment mean and standard deviation when grouped by sector.*

The above summary statistics reveal insights into the sentiment of tweets across various market sectors (Table 2). In the Consumer Discretionary sector, the mean sentiment scores indicate a predominantly negative sentiment, with both the Bing and Afinn libraries yielding below-zero mean values. That said, the wide standard deviations suggest significant variance in sentiment within this sector. In contrast, the Energy sector demonstrates a remarkably positive sentiment, as indicated by mean scores well above zero for both libraries. However, the small number of observations (7) in this sector raises questions about the statistical robustness of such a small sample.

High mean sentiment scores in tweets mentioning the industrial sector indicate an overwhelmingly positive sentiment (especially when using the Afinn library). The large standard deviations in this sector suggest considerable variation in the sentiment of tweets. Information Technology's mean scores are close to neutral, with slightly positive mean sentiment per the Afinn library.

Retweets

The summary statistics for retweets reveal that the dataset comprises 311 observations with a mean of 13,806 retweets and a standard deviation of 10,922 (Figure 5). The dataset's minimum and maximum values for retweets are 28 and 63,869, respectively. Future sections of this paper use a cutoff of 15,000 retweets to classify tweets into two groups: generally fewer or more retweets. I selected this threshold due to its proximity to the mean retweet count, providing a reasonable division for subsequent analysis.

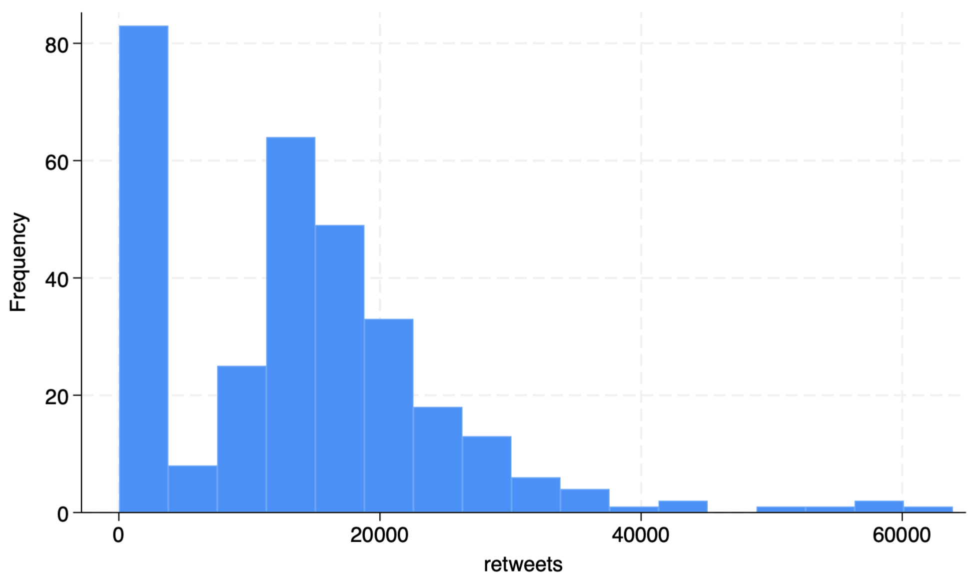


Figure 5. Distribution of Retweets. *Distribution of retweets for all 311 tweets in the sample.*

IV. Empirical Approach

The empirical approach employed in this study draws inspiration from established events study methods, using the Fama-French three-factor model for abnormal returns calculation and standard events study calculation methods for average abnormal returns and cumulative average abnormal returns. I selected this framework to provide valuable, replicable insights into the relationship between President Trump's tweets and stock market performance.

The event window used for this study is twenty days, encompassing ten days before and ten days after the tweet, falling within the recommended window by *Events Study Tools*. This window is made with the goal of capturing both market reactions and short-term trends. I used a 200-day estimation window (also within the suggested range) for the estimation window, with the goal of best capturing the stock's recent behavior for future prediction.

First, to quantify the impact of President Trump's tweets on stock market performance, I calculate abnormal returns (AR_{it}) as the residual of the actual minus expected returns, as suggested by MacKinlay (MacKinlay, 1997). This calculation uses the following formula:

$$AR_{i,t} = R_{i,t} - (R_{f,t} + \widehat{\alpha}_i + \widehat{\beta}_i (R_{m,t} - R_{f,t}) + \widehat{s}_p SMB_t + \widehat{h}_p HML_t)$$

Where AR_{it} is the abnormal stock return for an event on a specific date, $R_{i,t}$ is the stock's actual return on that date, $R_{f,t}$ is the risk-free rate, $\widehat{\alpha}_i$ is the intercept, and $\widehat{\beta}_i$ is the coefficient estimate of the excess market return ($R_{m,t} - R_{f,t}$). $\widehat{s}_p$ and $\widehat{h}_p$ are the coefficients for the difference in the total sample portfolio of tweets mentions *p* between small and big stocks (SMB_t) and high and low book-to-market stocks (HML_t) at time *t*, respectively. *SMB*, *HML,* and $R_{f,t}$ are all obtained from Dr. Kenneth R. French's Website (French, 2023). The model specification is based on a research article published in the Review of Quantitative Finance and Accounting (Choudhry, 2021). The Fama-French 3-Factor Model (Fama and French, 1993) is the prediction method of choice because it is commonly used, accurate, and straightforward.

These abnormal returns will serve as the basis for the subsequent analysis. Next, I compute the daily average abnormal returns (AAR) by aggregating the abnormal returns for all companies within the sample:

$$AAR_t = \frac{1}{n}\sum_{i=1}^{n} AR_{it}$$

Where n is the sample size and AR_{it} is the previously calculated abnormal returns for each event. To assess the cumulative impact of President Trump's tweets on individual stocks, I calculate the cumulative average abnormal returns (CAAR) by summing the daily average abnormal returns over the event window:

$$CAAR_{t_2} = \sum_{t=-10}^{t_2} CAR_t$$

The cumulative average abnormal returns provide an overview of the aggregate effect of tweets on stock market performance, summed over each day through a given t_2.

To evaluate the statistical significance of the findings, I employ a standard t-test, as widely applied in previous research. This statistical test allows us to determine whether the abnormal returns observed in response to President Trump's tweets are statistically significant.

While the methodology at this stage remains independent of sector-specific controls or retweet-related variables, this project's analysis will consider these factors in more detailed subsets of the data, as seen in Carl Ajjoub's 2020 paper that differentiates media and non-media companies as subsets when running their analysis (Ajjoub, 2020).

V. Results

All Tweets (no sentiment included)

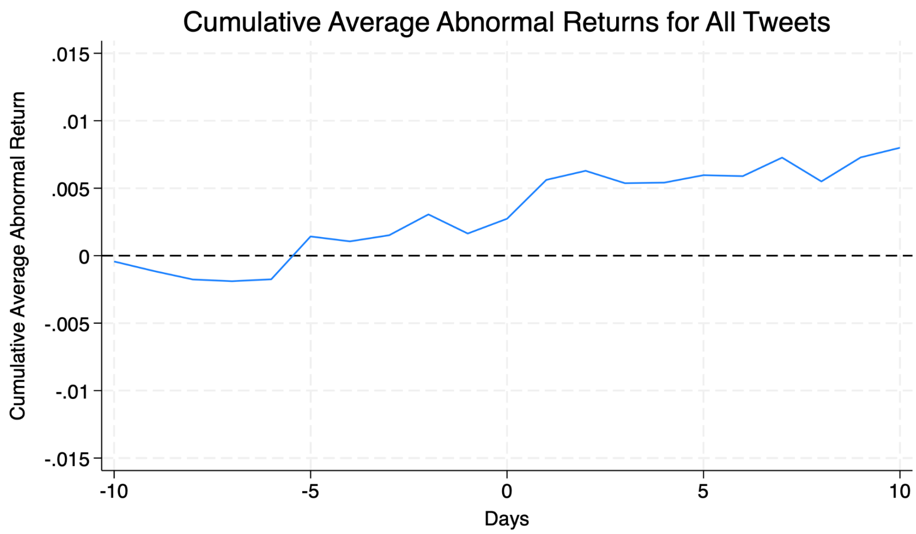


Figure 6. Cumulative Average Abnormal Returns for All Tweets. *Cumulative average abnormal returns for all tweets in the sample that mention S&P 500 companies. Arbitrary units are on the Y-axis (as it is an average of many stocks), and days before and after the tweet are on the X-axis.*

Without considering sentiment, the initial analysis yields a t-statistic of 1.72 with a p-value of 0.086, accompanied by a positive coefficient. This result indicates positive abnormal returns on the stock of companies that President Trump mentioned in his tweets. This result is statistically significant at the ten percent level. In other words, when ignoring the sentiment of the tweets, there is a noteworthy positive effect on the stock performance of the companies Trump mentioned in tweets.

One explanation for the positive abnormal returns observed when considering President Trump's tweets, irrespective of their sentiment, is that *any news is good news*. In the context of publicly traded companies, being mentioned by the President of the United States, a figure of immense influence could be viewed as a favorable event. It draws attention to the company, its products or services, and its place in the national or even global economy. The attention generated by such mentions often translates to increased visibility and discussion, which can attract investors and drive market activity. Even if the president expressed disagreement or criticism, the fact that a high-profile individual brought the company into the public discourse holds significance.

Furthermore, the idea that the President of the United States is interested in a particular company can be an implicit vote of confidence. It suggests that the company is on the radar of the highest office in the land, potentially reinforcing its position and credibility. Investors might interpret this as a positive signal, increasing the company's stock demand. In essence, the positive abnormal returns observed in this analysis align with the notion that any mention by the President, irrespective of sentiment, carries weight and can influence investor behavior.

Positive Tweets

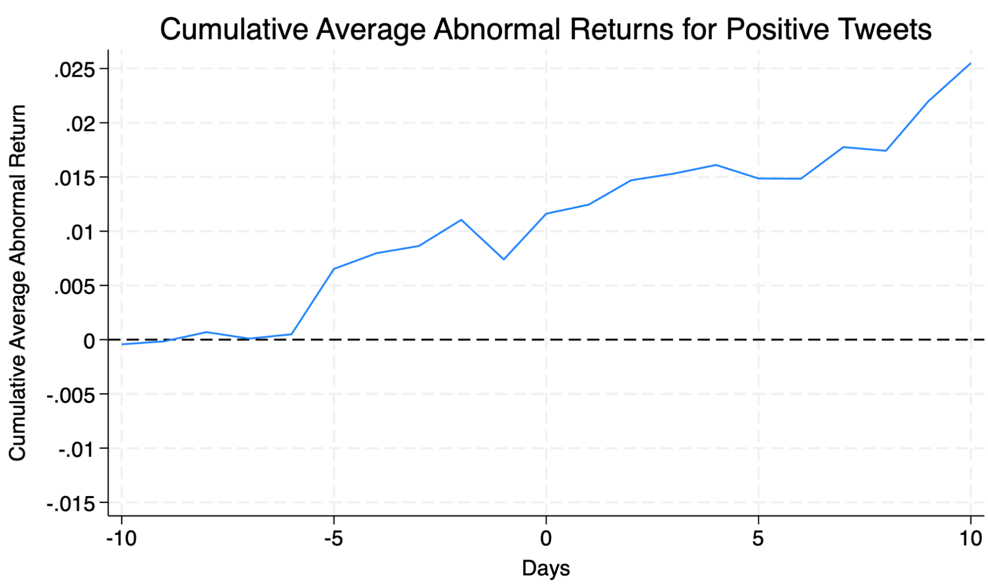


Figure 7. Cumulative Average Abnormal Returns (CAAR) for Positive Tweets. *Cumulative average abnormal returns for positive tweets in the sample that mention S&P 500 companies. Arbitrary units are on the Y-axis (as it is an average of many stocks), and days before and after the tweet are on the X-axis.*

When focusing solely on positive tweets, the analysis yielded a t-statistic of 2.61 with a p-value of 0.0103, accompanied by a positive coefficient. This result demonstrates that when considering tweets with a positive sentiment, there are positive abnormal returns on the stock of companies President Trump mentioned. This result is significant at the 5% level. The positive coefficient indicates that when the President expresses positive sentiment toward a company, it has a noticeable positive impact on its stock performance. Additionally, it is worth highlighting that the cumulative average abnormal return for these positive tweets is greater than when ignoring sentiment.

The observation of positive abnormal returns in this scenario aligns with intuitive expectations. When the President of the United States publicly expresses positivity about a company, investors view it as a vote of confidence. For investors, this signifies that the company is on the President's radar and receiving favorable attention. In this case, the positive sentiment reinforces the company's value and potential for growth. Investors are likely to interpret this as a favorable sign and may respond by increasing their investments in the company, driving up stock prices.

Negative Tweets

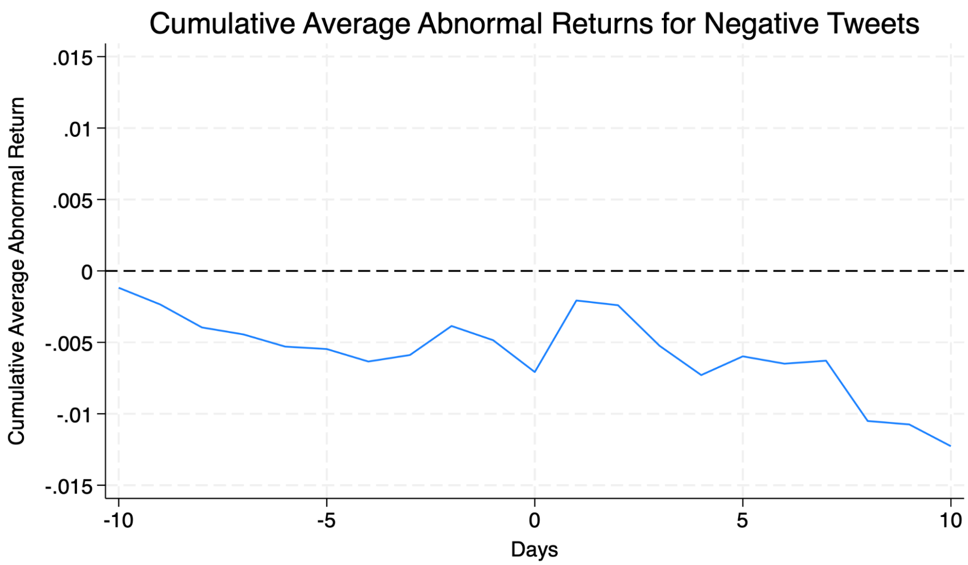


Figure 8. CAAR for Negative Tweets. *Cumulative average abnormal returns for negative tweets in the sample that mention S&P 500 companies. Arbitrary units are on the Y-axis (as it is an average of many stocks), and days before and after the tweet are on the X-axis.*

When focusing solely on negative tweets, the analysis yielded a t-statistic of -1.77 with a p-value of 0.079 and a negative coefficient. This result is significant at the ten percent significance level. This result indicates that when considering tweets with negative sentiment, there are negative abnormal returns on the stock of companies Trump mentioned. This result also aligns with what one might intuitively expect, as it suggests that when the President expresses negative sentiments about a company, it may hurt that company's stock performance.

Observing negative abnormal returns in response to President Trump's negative tweets aligns with intuitive expectations. When the President of the United States expresses negative sentiments about a company, investors potentially interpret it as a signal of concern or criticism, which is significant given his influential position and access to information. Negative tweets may also indicate issues or challenges within the company that have caught the President's attention, which could lead to concerns about the company's prospects and financial health. In response to such negative sentiments, investors may decide to sell their shares, leading to a dip in stock prices.

Furthermore, the reasoning that "any news is good news" may also apply here. While the result is statistically significant, it is possible that negative tweets generated both positive and negative market activity. This lower magnitude may explain why the negative effect is smaller than the positive effect following positive tweets.

Tweet Reach

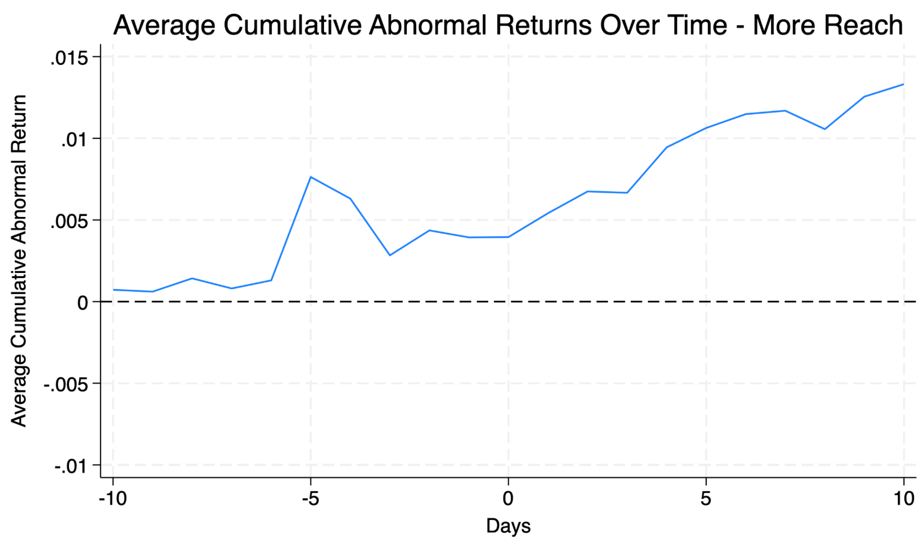


Figure 9. CAAR for Tweets with More Reach. *Cumulative average abnormal returns for tweets in the subsample of at least 15,000 retweets that mention S&P 500 companies. Arbitrary units are on the Y-axis (as it is an average of many stocks), and days before and after the tweet are on the X-axis.*

When focusing on tweets with more reach (over 15,000 retweets), the analysis yielded a t-statistic of 2.30 (p-value of 0.023) and a positive coefficient. This result indicates that tweets with more reach generated significant positive abnormal returns on the stock of the mentioned companies, significant at the five percent level. On the other hand, tweets with less reach (fewer than 15,000 retweets) had a t-statistic of 0.01 and a corresponding p-value of 0.989. Therefore, there is insufficient evidence to prove that tweets made by President Trump with fewer retweets generated significant abnormal returns on the stock of the mentioned companies.

This result makes intuitive sense. Tweets with higher reach are likely to be seen by many people, including investors, analysts, and traders. This widespread visibility can significantly impact stock prices due to the information and sentiment conveyed in the tweet. On the other hand, tweets with fewer than 15,000 retweets likely have a much smaller audience. As a result, they are less likely to cause notable changes in investor behavior or market sentiment, leading to the observed lack of significant abnormal returns on the stocks mentioned. Furthermore, a tweet with many retweets is likely to be disseminated more quickly and widely, potentially influencing stock prices faster and more significantly than less popular tweets.

Reach and Sentiment Combined

When following a method of events study calculation proposed by Dr. Steffen Erikson, an economist from the Netherlands' University of Groningen, it is possible to include multiple control variables simultaneously (Erikson, 2022). This is made possible by running a test including multiple control variables and then paying attention to the appropriate t-tests for each variable. I ran this analysis, including both the retweets and sentiment library scores, and found the following results:

	Coefficient	Std. Error	t-statistic	P > |t|
Retweets	≈ 0	≈ 0	-0.66	0.509
Bing	0.004	0.002	1.89	0.059
Constant	0.011	0.006	1.72	0.086
Retweets	≈ 0	≈ 0	-0.71	0.477
Afinn	0.001	0.0009	1.48	0.14
Constant	0.011	0.006	1.66	0.099

Table 3. T-tests, including retweets and sentiment score controls. *The following findings are displayed: coefficient, test (t) statistic, and p-value for whether the subset of each sector displays cumulative abnormal returns significantly different from zero. Note that values are rounded to three decimal places, which is why the t- statistic, and p-values are slightly different for the constant. I ran this test twice, one time for each sentiment library.*

The above results show that in the presence of sentiment score, for both the Bing and Afinn libraries, the reach of the tweet is no longer significant, an interesting finding compared to the previous section. Upon further consideration, this makes logical sense. In both cases, I still find significant cumulative abnormal returns (as shown in the constant row) at the ten-percent level. In addition, the Bing and Afinn tests show a positive coefficient for the sentiment library score, implying that the cumulative abnormal returns move with the sentiment of the tweet. This result is significant at the ten-percent level in the case of the Bing library and not statistically significant in the case of the Afinn library.

In addition to the above-reported results, I also investigated interaction terms between the sentiment scores and the number of retweets. In both cases, the interaction term was non-significant at the ten percent level and did not add to the analysis. This further supports the idea that the reach of a tweet is not a significant predictor of abnormal returns when the tweet sentiment is present.

Market Sector Subsamples (split by sentiment, sample size allowing)

Sector	Observations	t-statistic	P > |t|
Consumer Discretionary (positive)	55	1.89	0.065
Consumer Discretionary (negative)	102	-2.22	0.029
Information Technology (positive)	23	1.21	0.238
Information Technology (negative)	22	-0.13	0.899
Energy	7	9.55	≈ 0
Financials	3	1.23	0.343
Health Care	9	1.04	0.328
Industrials	19	-0.71	0.485
Telecommunications	3	-5.10	0.036

Table 4. CAAR Significance by Market Sector. *Test (t) statistic and p-value for whether the subset of each sector displays cumulative abnormal returns significantly different from zero. Sectors with a large number of observations (namely Consumer Discretionary and Information Technology) are additionally divided by sentiment.*

The market sector-specific analysis reveals interesting insights into the impact of President Trump's tweets on the stock market performance of companies within different sectors. Notably, the Consumer Discretionary also exhibited significant results, with positive tweets positively impacting abnormal returns with a t-statistic of 1.89 and a p-value of 0.065. For negative Consumer Discretionary tweets a test statistic of -2.22 and a p-value of 0.029 is observed.

For the other sectors, namely Information Technology, Financials, Health Care, Industrials, and Information Technology, the results do not reach statistical significance. That being said, although the Information Technology sector has non-significant results for both positive and negative tweets, the direction of the abnormal returns follows what one would expect (positive tweets having a non-significant positive impact and the opposite impact for negative tweets). It is also worth noting that some of these sectors have small sample sizes, and future studies could use a nonparametric approach to understand the true effect of President Trump's tweets on stock returns. The Energy sector shows extremely high and significant abnormal returns but because the sample size (7) is so small, I am hesitant to draw strong conclusions. Similarly, the telecommunications sector shows strong negative cumulative abnormal returns but only has a sample size of three.

The varying effects observed across different sectors can be attributed to many factors. For the Financial sector, the significant and positive impact is potentially related to the President's unique access to information relating to the economy, to which financial companies are closely tied. The energy sector, for example, also includes high levels of government regulation which could also provide the President with unique information not available to investors. There are a plethora of other potential reasons that could be further investigated in future studies, and one could find very interesting results when considering each market sector's defining characteristics.

VI. Future Improvements

One notable shortcoming of this study is the small number of tweets mentioning some market sectors. Because of this, I hesitate to accept some of the market-specific results due to the small sample sizes. I would be very interested in seeing future research utilize a nonparametric approach to solving this problem.

Another consideration outside of this research's scope is how other politicians' social media activity relates to the movement of markets. Does this also extend to prominent leaders of companies? *Looking at you, Elon Musk!* Expanding this type of study to more than just one person would be a major improvement. Unfortunately, because of Twitter's recent API changes, it may not be feasible at a realistic cost, but regardless it would be a fascinating analysis.

Finally, comparing the portfolio of politicians' stock to the companies they mention on social media would lead to another interesting research project. A Portfolio breakdown combined with sentiment analysis and many more future studies could all build upon the existing research.

VII. Conclusion

This study delved into this evolving landscape by examining the influence of President Donald Trump's tweets on the stock market performance of publicly traded companies. Through an extensive analysis, I sought to comprehend the intricate relationship between presidential tweets, market reactions, and the potential need for regulatory measures.

The investigation commenced with a broad exploration of President Trump's tweets without considering their sentiment. This initial analysis revealed a notable positive impact on the stock performance of companies mentioned in his tweets, even when sentiment was not part of the equation. This finding supports the notion that any news about a company emanating from the President, regardless of sentiment, holds weight in financial markets. Such attention can potentially drive investor behavior and influence stock prices.

When considering tweets with positive sentiment, I observed a more pronounced positive effect on stock performance, reaching statistical significance at the five-percent level. Positive tweets conveyed a strong vote of confidence in the mentioned companies, reinforcing their value and potential for growth. The influence of presidential positivity highlighted the considerable impact of sentiment, even when focused on positive expressions, and its capacity to influence investor behavior.

Conversely, tweets with negative sentiment adversely affected stock performance, again reaching statistical significance at the ten-percent level. Negative tweets from the President could be perceived as a signal of concern or criticism, potentially leading to decreased investor confidence and stock prices. The results indicated the potential impact of negative sentiments expressed by influential figures on market behavior.

Then, I examined the role of retweets in influencing stock performance. Tweets with more retweets (greater than 15,000) generated significant positive abnormal returns, shedding light on the impact of higher-reach tweets. However, retweets were no longer significant when including sentiment score, tweet reach, and also testing for interaction. This finding could be because investors interested in Trump’s tweets will read them regardless of the reach. There remains area for further investigation though, as future studies could introduce new controls to add to the models. This may uncover new insights into the true relationship between these variables.

The exploration then extended to sector-specific analyses, revealing sector-dependent variations in the impact of presidential tweets. Various results were found, with the Consumer Discretionary sector finding significant abnormal returns and the Information Technology sector finding non-significant returns when also including sentiment. The other sectors had mixed results but I am hesitant to draw conclusions due to small sample sizes.

In conclusion, this study adds to the growing research on the connection between social media and financial markets. The findings show the influence of presidential tweets, even when ignoring sentiment, and the varying impacts of positive and negative sentiment on stock performance. Moreover, the analysis of retweets and sector-specific effects provides valuable insights into the complexity of this relationship. This work also highlights the need for future research to delve deeper into the sector-specific dynamics.

Furthermore, the potential need for regulation is evident. While it is essential to protect the freedom of expression of political figures, there is a growing concern about the impact of their messages on financial markets. I would recommend an inquiry into establishing a House or Senate committee to monitor and ensure that all U.S. politicians adhere to ethical guidelines in their social media communication. This oversight would help maintain transparency and accountability in a rapidly evolving digital landscape, safeguarding the integrity of financial markets without infringing on the right to free speech. As the digital age continues to shape market dynamics, empirical economics must adapt and expand to comprehensively explore the impact of social media communication on financial markets, regulation, and investor behavior.

VIII. Acknowledgments

Thank you to Professor P. J. Glandon for guidance throughout this project. Thank you to Tucker Fulton for reviewing the first draft and the entire Advanced Econometrics Seminar at Kenyon College for general advice and recommendations on best conducting this study. Julia Sigle's "Tidy Text Mining with R" provided valuable data processing insights.

IX. References

Ajjoub, Carl, et al. “Social Media Posts and Stock Returns: The Trump Factor.” *International Journal of Managerial Finance*, vol. ahead-of-print, no. ahead-of-print, 3 June 2020, https://doi.org/10.1108/ijmf-02-2020-0068.

Ballhaus, Rebecca. “President Trump’s Tweets Have Companies Playing Defense” *The Wall Street Journal*, 13 February 2017, https://www.wsj.com/articles/president-trumps-tweets-have-companies-playing-defense-1486981801

Brans, Heleen, and Bert Scholtens. “Under His Thumb the Effect of President Donald Trump’s Twitter Messages on the US Stock Market.” *Plos One*, vol. 15, no. 3, 11 Mar. 2020, p. e0229931, https://doi.org/10.1371/journal.pone.0229931.

Burke, Michael. “Schultz says he won’t respond to Trump’s ‘childish’ tweet” *The Hill*28 January 2019, https://thehill.com/homenews/campaign/427376-schultz-says-he-wont-respond-to-trumps-childish-tweet/

Christenson, Dino, et al. “Going Public in an Era of Social Media: Tweets, Corrections, and Public Opinion” *Presidential Studies Quarterly*, vol. 51 no. 1 November 2020, pp. 151-165 https://onlinelibrary.wiley.com/doi/abs/10.1111/psq.12687

Choudhry, Taufiq et al. “Loss Sensitive Investors and Positively Biased Analysts in Hong Kong Stock Market”. *Review of Quantitative Finance and Accounting*. Vol. 57 no. 3, April 2021, https://www.researchgate.net/publication/349027981_Loss_Sensitive_Investors_and_Positively_Biased_Analysts_in_Hong_Kong_Stock_Market

Erikson, Steffen. “A step by step guide on how to conduct an event study.” YouTube, Nov 7, 2022, https://www.youtube.com/watch?v=DvZ9B7XyyTw.

Event Study Tools. “Event Study Application Blueprint” *Event Study Tools* np. nd. , https://www.eventstudytools.com/event-study-application-blueprint#:~:text=On%20the%20one%20hand%2C%20information,days%20(Holler%2C%202014)

Fama, Eugene F. and French, Kenneth R. “Common risk factors in the returns on stocks and bonds” *Journal of Financial Economics* vol. 33, pp. 3-56, 1993, https://www.bauer.uh.edu/rsusmel/phd/Fama-French_JFE93.pdf

French, Kenneth R. “U.S. Research Returns Data” *Kenneth R. French Website*, 2023, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

Gordon, M. J. “Dividends, Earnings, and Stock Prices” *The Review of Economics and Statistics*, 1959, https://www.jstor.org/stable/1927792. Accessed 2024

He, Ziyu. “Macroeconomic Research with Innovative Methods.” *Escholarship.org*, 2021, escholarship.org/uc/item/89x826bj. Accessed 2023.

Juma’h, Ahmad H., and Yazan Alnsour. “Using Social Media Analytics: The Effect of President Trump’s Tweets on Companies’ Performance.” *Journal of Accounting and Management Information Systems*, vol. 17, no. 1, 1 Mar. 2018, pp. 100–121, https://doi.org/10.24818/jamis.2018.01005.

MacKinlay, Craig M. “Events Studies in Economics and Finance.” *Journal of Economic Literature*, vol. 35, no. 1, March 1997, pp 13-29, https://www.jstor.org/stable/2729691?casa_token=Wd4llHssgHEAAAAA%3AiCWTNlYPy--JClhKOulda3dWpaH-iAZA4Q5IB_1r9_X_03NFzwWwWfzp1Epj6ziRZCjLVjSN57XMVYzCqaBzUIeODmm0BEewKftKI0HtvhwpE-FnnZo&seq=3

Mazetti, Mark “The Poisoned Relationship Between Trump and the Keepers of U.S. Secrets” *New York Times*, August 11, 2022, https://www.nytimes.com/2022/08/11/us/politics/trump-fbi.html

Minot, Joshua et al. “An exploration of public engagement with Obama and Trump on Twitter” *Plos 1*, April 14, 2021, https://www.pewresearch.org/journalism/2021/11/15/news-on-twitter-consumed-by-most-users-and-trusted-by-many/

Mitchell, Amy et al. “News on Twitter: Consumed by Most Users and Trusted by Many” *Pew Research Center*, Nov 15, 2022, Mitchell, Amy et al. “News on Twitter: Consumed by Most Users and Trusted by Many” Pew Research Center, Nov 15, 2022, https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0248880

Yasseri, T. et al. “How are social media changing democracy?” *The Economist*, 28 March 2016, pp. https://www.economist.com/the-economist-explains/2016/03/28/how-are-social-media-changing-democracy.

Yen, Meng-Feng, et al. “A Two-Dimensional Sentiment Analysis of Online Public Opinion and Future Financial Performance of Publicly Listed Companies.” *Computational Economics*, vol. 59, no. 4, 20 June 2021, pp. 1677–1698, https://doi.org/10.1007/s10614-021-10111-y. Accessed 4 Oct. 2023.