The Impact of Donald Trump's Tweets on Financial Markets

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This Dissertation is presented in part fulfilment of the requirement for the completion of an Undergraduate degree in the School of Economics, University of Nottingham. The work is the sole responsibility of the candidate.

I am happy for this dissertation to be made available to students in future years if chosen as an example of good practice.

Abstract:

This study tests the efficient market hypothesis (EMH) by analysing the effect of Donald Trump's company-specific tweets on financial markets for the period between 8 November, 2016 (the U.S. presidential election date) to 24 January, 2018 (a year after inauguration). Using a sample of 24 company-specific tweets, the results show that a tweet by Trump leads to statistically significant abnormal returns that last for 2 to 3 trading days. This is inconsistent with the semi-strong form of EMH. This is the first paper to test the attention-based investing hypothesis by Barber and Odean (2005) using Trump's tweets. Attention-based investing is a possible reason for market inefficiency as Trump's tweets lead to an abnormal trade volume of 43.54% on the day of the tweet and an increase in Google search activity on the week of the tweet.

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1. Introduction

The social networking platform Twitter was established in 2006. It has since grown in popularity with over 330 million active users (Statista, 2018). An avid user of Twitter is Donald Trump. Recently elected as the 45th President of the United States, Trump, unlike his 44 predecessors, actively uses Twitter to express his views on global affairs. One would think that Trump uses Twitter to build support for his campaign however, Trump is renowned for using Twitter as a strategic tool to prevent US companies from moving operations overseas and publicly berating political leaders. With over 50 million followers on Twitter, Trump has become the most followed world leader and investors are now closely monitoring his tweets as indicators of future policy. This gives Trump exclusive power to influence financial markets with just 140 characters, as shown below:

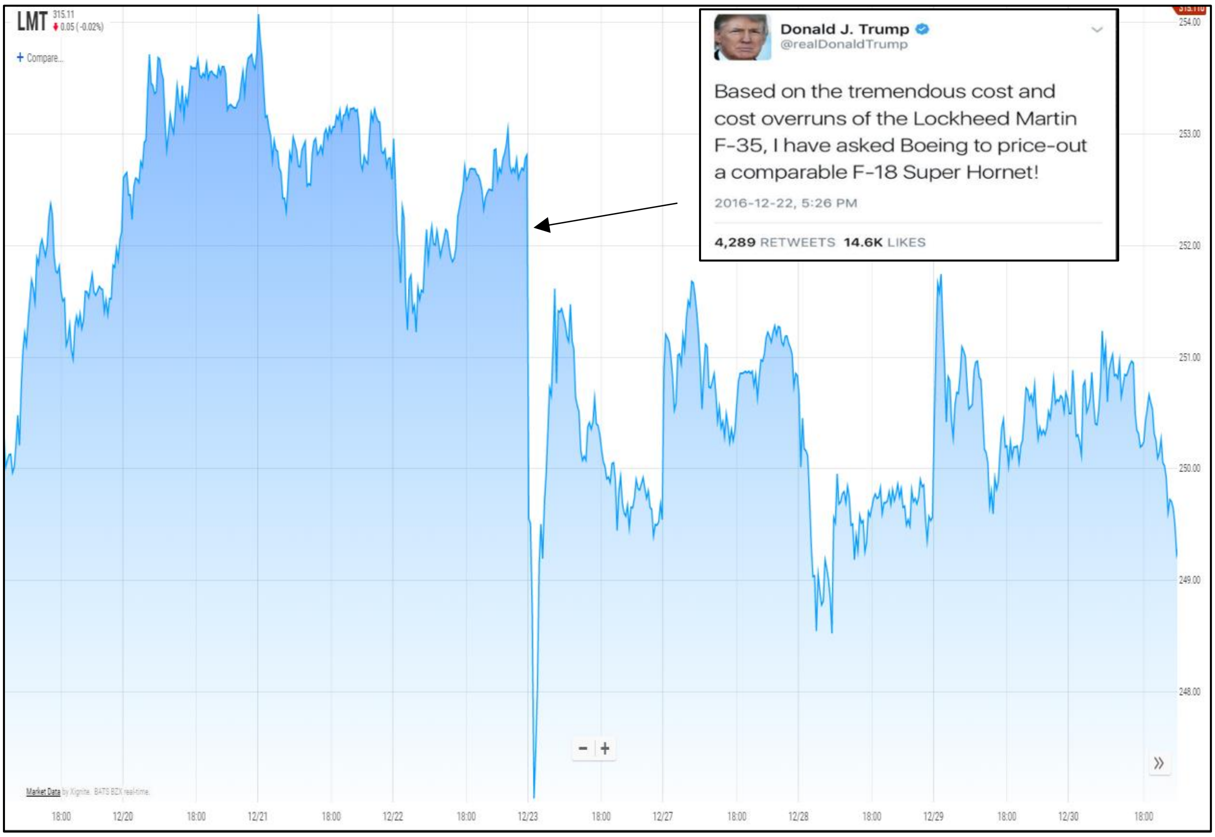

Figure 1: 1-minute chart of Lockheed Martin's (LMT) stock price.

Trump tweeted about Lockheed Martin on 22 December, 2016 after the market had closed. The next trading day, Lockheed Martin's stock price dropped by 2% and this decreased its market value by $1.2 billion. Trump may have been able to move the market this much because investors feel Lockheed Martin will be targeted by Trump in future policy and therefore this new information is reflected today through a decrease in its stock price. Figure 1 also shows that the stock recovered on the same day. This may imply markets rapidly incorporate new information and thus the efficient market hypothesis (EMH) holds.

On the other hand, some of Trump's tweets are non-informative. For instance, Trump responded to Nordstrom's announcement of removing Ivanka Trump's clothing line:

@realDonaldTrump: "My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person – always pushing me to do the right thing! Terrible!"

This tweet merely draws attention to Nordstrom's actions and is non-informative. Immediately after the tweet, Nordstrom's stock plummeted by -0.3%. However, after just 4 minutes (Marketwatch, 2017) the stock price recovered and at market close, the stock price had actually increased by 4%. The fact that the market reacts to a non-informative Trump tweet, suggests that the EMH does not hold. A possible explanation of these movements is Trump's tweets catch the attention of retail investors[1] who cannot process all available information. This paper tests this hypothesis.

These examples highlight that analysing the impact of Trump's tweets on financial markets is a unique way of testing the EMH. Specifically, this paper will first test the hypothesis that a positive (negative) Trump tweet leads to a higher (lower) stock return. The study will then test whether stock prices rapidly incorporate the informational content of Trump's tweets, thus testing the semi-strong form of the EMH. Finally, this paper tests the attention-based investing hypothesis by Barber and Odean (2005) through analysis of trading volume and Google search activity.

2. Background

Eugene Fama (1965) pioneered the EMH, which states that all available information at a certain time is fully incorporated into security prices. The intuition behind this is that, in the absence of frictions, this information disperses so quickly that security prices adjust before an investor has time to trade. There are three forms of the EMH; the semi-strong form is analysed in this paper. This form states that all public announcements are priced into the market. Public announcements may include earnings announcements and dividend changes. By classing Trump's tweets as public announcements, the semi-strong form of EMH is tested.

The literature review shows that there is no consensus on whether the EMH holds in practice. One possible reason for this is that the EMH assumes that investors consider all available

[1] A retail investor is a non-professional investor that trades for personal reasons rather than for an institution. They tend to trade in much smaller amounts than institutional investors do. They have fewer resources to work with.

information when investing. When choosing what to invest in, investors have the option of many different stocks. Barber and Odean (2005) suggest retail investors have high search costs and therefore are likely to only consider information that grabs their attention rather than all available information. On the other hand, institutional investors are less prone to indulge in attention-based purchases as they have relatively more time and resources. This means that the EMH does not hold, as some investors do not consider all available information. This study will test this hypothesis by analysing abnormal trading volume to assess whether a tweet by Trump does actually generate investor attention. Furthermore, this study will contribute to Barber and Odean (2005) as it will monitor the Google search activity of these stocks during Trump's tweets. Google search activity determines whether small retail investors act upon Trump's tweets and drive market inefficiency, assuming small retail investors are likely to use Google to search for stocks, unlike institutional investors who will use Bloomberg Terminals.

3. Literature Review

The EMH appears frequently in economic literature. A common methodology used to test the EMH is event studies[2]. This dissertation also uses event studies and therefore, the review starts by comparing key event study papers. These papers tend to analyse the effect of financial announcements, such as stock splits, on markets. Recently, Economists have focused on the impact of non-financial announcements, such as social media posts, on stock markets to test the EMH. Trump's tweets are non-financial announcements and therefore key papers that analyse the effect of these specific announcements on financial markets will be the focus of the latter parts of the review.

Fama, Fisher, Jensen and Roll (1969) were the first to test the semi-strong form of EMH using event studies. They analysed the impact of stock splits[3] on stock prices using monthly data. They pioneered the market model[4] in order to control for general market movements and focus purely on the effect of the stock split announcement. In the pre-announcement period, the returns on stocks are very high. This is because these companies have experienced dramatic increases in expected earnings and dividends, leading to an increase in stock price (hence the need for the stock split). The returns on these securities are even higher a few months after the split. This implies that the market is inefficient as it takes time to incorporate this new information. However, the authors note that co-existing events could be driving stock price changes. More

[2] Event studies are a statistical method used to measure the impact of an event on a firm's value or stock price
[3] A stock split is a way of reducing the stock price of the company in order to make the stock more affordable to investors.
[4] A market model is a statistical method of finding expected returns of stocks. It is devised through a regression, which will be shown in the methodology section.

specifically, dividend payments usually change after a stock split and therefore this may affect the stock price. Once they control for dividend announcements, abnormal returns[5] are insignificant for periods after the stock split announcement. This means that the market is efficient as stock prices adjust rapidly to new information. Similarly, this dissertation uses event studies and the market model to test stock market efficiency. In contrast, instead of using monthly data, this study uses daily data as Trump is likely to have a short-term effect on stock prices. This paper by Fama et al. (1969) initiated an array of research on the effect of different types of public announcements on financial markets such as dividend policy changes and quarterly earnings announcements.

Charest (1978) analysed the impact of dividend changes on the stock prices of New York Stock Exchange (NYSE) companies over the period 1947-1967. He finds that an increase in cash dividend leads to abnormal returns of 1%. A decrease in cash dividend leads to abnormal returns of -3.18%. He suggests there is a stronger negative effect as a decrease in cash dividend announcement is usually in the wake of other bad news. Moreover, he finds significant abnormal returns in the months following dividend changes. This implies the market is inconsistent with the semi-strong form of EMH. Similarly, Ball and Brown (1968) found evidence inconsistent with the semi-strong form of EMH. However, they analysed the impact of annual corporate earnings announcements on security prices. They found that stock prices do not fully incorporate new information instantly and abnormal returns are present many days after the announcement. They call this the post earnings announcement drift (PEAD) and it represents the delay in stock price adjustment to equilibrium levels. Bernard and Thomas (1989) test the EMH through analysis of quarterly earnings announcements on stock prices. Similarly, to Ball and Brown (1968), they find a PEAD of 60 days. Therefore, these findings are inconsistent with the EMH. Many studies analyse the impact of financial announcements on stock markets. This dissertation contributes to the existing literature by focusing on a non-financial announcement. Specifically, it focuses on how social media posts can affect financial markets.

The growing influence of media and social media has led to a flurry of research into the impact of media on financial markets. Tetlock (2007) analyses the interactions between a popular Wall Street Journal column and the stock market. In this journal column, brokerage houses, Analysts and other professionals give their views on stocks. By categorising the content of these columns into pessimistic, negative and weakly negative, he finds that high values of media pessimism lead to temporary downward pressure on corresponding stock prices and temporarily high values of

[5] Abnormal returns are the actual returns of a stock minus the expected returns of a stock (which is calculated through the market model).

trading volume. This downward pressure lasts for two trading days. After making a fair assumption that these newspaper columns are non-informative about the fundamentals of the company, he argues that the market is inconsistent with the semi-strong form of EMH. Ranco et al. (2015) instead analyse the impact of Twitter on markets. During U.S. earnings season, a positive tweet leads to a cumulative average abnormal return (CAAR)[6] of 4.22% on the day of the tweet whereas a negative tweet leads to a CAAR of -5.64%. These effects last for up to 10 days after the tweet, implying inconsistency with the semi-strong form of the EMH. Similarly, positive tweets posted during non-earnings periods lead to a CAAR of 3.65% whereas negative tweets lead to a CAAR of -3%. These effects last for up to 8 days after the tweet. This confirms that the EMH does not hold. Similarly, this dissertation analyses the impact of social media on financial markets, however it focuses on one Twitter user, namely Donald Trump. Ranco et al. (2015) show that including earnings announcement periods lead to an inflated figure for abnormal returns. Therefore, in this study, Trump's tweets that occur during earnings season are excluded in order to find the exact impact of a Trump tweet.

Malaver and Vojvodic (2017) focus on the effect of Trump's tweets on the Mexico Peso against the U.S. Dollar. They analyse the impact of 7,429 Trump tweets between June 16, 2015 and February 21, 2017. The results show that a negative tweet by Trump leads to an increase in the daily volatility of the Mexican Peso against the U.S. Dollar by 21.6%. This shows that Trump can influence foreign exchange markets. This dissertation will focus on stock markets rather than the foreign exchange market as methods for testing the EMH in foreign exchange markets are not as widely documented as methods for testing the EMH in stock markets.

Born, Myers and Clark (2017) test the semi-strong form of EMH by analysing the impact of Trump's tweets on stock markets. They analyse stock returns during the president-elect period[7]. The results show that CAAR are statistically significant for five trading days after the tweet, implying inefficient markets. They also compute abnormal trading volume and Google search activity in order to monitor whether noise trading is present. They find that the pattern of trading volume and Google search activity implies small noise traders are reacting to Donald Trump's tweets and therefore driving market inefficiencies. A caveat of this paper is a small sample size of only 15 tweets. Ge, Kurov and Wolfe (2017) build upon the limitation of Born et al. (2017) by considering a larger sample size of 48 tweets. They consider tweets from the pre-

[6] Cumulative average abnormal returns are simply the sum of average abnormal returns over the event window. This is used to test how long it takes markets to incorporate new information.

[7] The president-elect period is a period between the election date and inauguration whereby a candidate has won the election but has not entered office yet. For Trump, this period was between November 8, 2016 and January 20, 2017.

inauguration and post-inauguration period[8] rather than just the president-elect period. Using event studies, they find that positive and negative Trump tweets, on average, move stock price by 0.80% and there is no asymmetry in the impact of positive and negative tweets. They find abnormal returns are statistically significant for 2 days after the tweet. This is inconsistent with the semi-strong form of EMH. A limitation of event study methodology is that co-existing events could move stock prices and therefore have an impact on the sample of stocks. For instance, preceding company or earnings announcements may cause misinterpretation of the impact of Trump's tweets. These papers do not consider the effect of earnings and company announcements that occur in proximity to Trump's tweets. Ge et al. (2017) note that only 18 out of the 48 presidential tweets do not have preceding related news events. To build upon these limitations, this dissertation categorises Trump's tweets into informative and non-informative tweets. Informative tweets are used to test the EMH and non-informative tweets will be discarded from the sample.

To summarise, this dissertation is building upon the limitations of previous literature. The sample size of Trump's tweets is increased by increasing the sample range. 24 tweets are obtained, which is an enlargement of the sample size of previous literature[9]. Furthermore, a subsample of Trump's tweets that are not responses to company announcements and do not occur during earnings announcements is created. This subsample is used to test the EMH. The key contribution of this paper to existing literature is the explanation for why markets may be inefficient. More specifically, analysis of abnormal trading volume and Google search activity provides insight on whether Trump's tweets lead to attention-based investing, which in turn drives market inefficiency.

4. Data

4.1. Tweet Collection

An algorithm devised by Twlets.com is used to collect a full sample of Trump's company-specific tweets. Tweets posted by Donald Trump's personal account (@realDonaldTrump) are used rather than Donald Trump's presidential account (@POTUS) as Trump simply retweets his personal account tweets on his presidential account and hence activity on this account provides no new information.

[8] Inauguration, in this case, is the ceremony to mark the start of Donald Trump's presidency. The ceremony was held on January 20, 2017.
[9] Considering Ge et al. (2017) have only 18 informative tweets.

4.2. Financial Data Collection

Yahoo Finance is used to access historical daily prices of stocks and logarithmic daily stock returns are calculated using the formula:

$$R_{i,t} = \frac{\ln(P_{i,t})}{\ln(P_{i,t-1})}$$

Where ($R_{i,t}$) is the daily returns of stock i at time t, $P_{i,t}$ is the closing price of stock i at day t and $P_{i,t-1}$ is the previous day's closing price for stock i.

The stocks used are the ones mentioned by Trump in his company-specific tweets. Daily data is used rather than intraday data as daily data is more accessible and also Trump occasionally tweets after the market closes so the effect is evident on the next trading day. Furthermore, Trump tends to tweet about two companies on the same day due to the 140-character limit and daily returns combines the effect of both tweets on the stock. Similarly, the daily trading volume data across firms is collected through Yahoo Finance.

4.3. Sentiment Classification

Sentiment analysis is undertaken via an algorithm called valence aware dictionary and sentiment reasoner (VADER). VADER is a reliable method for calculating the polarity of tweets as it is used frequently to analyse social media. VADER has a dictionary of social media vocabulary and matches words in tweets with this dictionary. It assigns a compound value to tweets and categorises tweets as positive, negative and neutral. Here is an example of VADER analysis on one Donald Trump tweet:

@realDonaldTrump: "Thank you Brian Krzanich, CEO of @intel. A great investment ($7 BILLION) in American INNOVATION and JOBS!"

The VADER analysis assigns this tweet a compound score of 0.8814. The sentiment score of each tweet is compounded and standardised between 1 and -1 with 1 being extremely positive, -1 being extremely negative and 0 being neutral. As can be seen, VADER does well in accurately identifying the sentiment in the above tweet and classing it as a very positive tweet. Trump's tweets are classified into positive and negative sentiments in this manner (see appendix C).

5. Methodology

5.1. Event Studies

The first step of conducting an event study is to define the event window. The event window is the time interval over which the event occurs. This can include a certain number of days before and after the announcement.

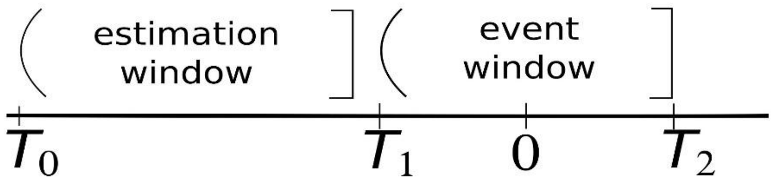

Figure 2: Event study timeline

This timeline defines the key periods in an event study. On the timeline, $t = 0$ is the day that the tweet occurs. This is the event day. The event window is T_1-T_2 where T_1 is the first day in the event window and T_2 is the last day. There is no consensus on the length of the event window. In existing event study literature, the event window varies from 1 to 40 days. Born et al (2017), who also measure the effect of Trump's tweets on financial markets, incorporate a 10-day event window ranging from day -5 (5 days before the announcement) to day 5 (5 days after the announcement). A 20-day event window, which analyses average abnormal returns on day -10 and day 10, is incorporated in this study. I use a longer event window than Born et al. (2017) to confirm there are no preceding events that affect stock returns.

The second step of an event study is to define the estimation window. The estimation window is the interval of time before the event window that is used to estimate the expected (or normal) returns. When selecting the estimation window, it is usually common practice, according to Peterson (1989), to pick an estimation window with a length of 100 to 300 days. The more days we use, the more accurate the estimation parameters are likely to be. In this study, the estimation window starts from day -271 and ends on day -21. Therefore, the length of the estimation window is 250 trading days. There is gap of 10 days between day -21 and day -11, in order to prevent the tweet from influencing the expected return parameters.

5.1.1. Sample Selection

The second step of conducting an event study is to define the sample. Firstly, Trump tweets a significant number of times to the New York Times (NYT). Over the sample period, he sent 42 negative tweets to the NYT. It is assumed that markets have factored in Trump's negative stance on NYT and therefore these tweets are excluded from the sample. Ge et al. (2017) and Born et al. (2017) also exclude these tweets. A limitation of event studies is that the results on day 0 could be driven by preceding events such as earnings and company announcements. In this study, company announcements do occur in proximity to a minority of Trump's tweets. For instance:

@realDonaldTrump: "Thank you to @exxonmobil for your $20 billion investment that is creating more than 45,000 manufacturing & construction jobs in the USA!"

The fact that Exxon are investing $20 billion may lead to an increase in their stock price itself and therefore if this tweet is included in the sample, the effect of Trump's tweet would be biased upwards by this company announcement. Therefore, tweets that are responses to company announcements (henceforth 'response tweets') are excluded from the sample as these tweets do not contain new information. Similarly, a better-than-expected earnings announcement may lead to an increase in stock price and therefore bias the effect of Trump's tweets on stock prices. Therefore, Trump's tweets which are in a 20-day proximity to earnings announcement dates (see appendix B) are excluded from the sample when testing the EMH.

Overall, the full data sample contains 44 Trump tweets observed between 8 November, 2016 (the US presidential election date) to 24 January, 2018 (a year after inauguration). 15 tweets are response tweets, 4 tweets occur during earnings announcements and 1 tweet occurs during a takeover announcement. These 20 tweets are excluded from the sample. The remaining 24 tweets are informative and this subsample is used to test the EMH. These tweets are categorised as positive or negative through sentiment analysis and overall we find that out of the 24 tweets, there are 16 negative tweets and 8 positive tweets.

5.1.2. Normal & Abnormal Returns

Now that the estimation period is defined and the sample is selected, the normal (or expected) returns of each stock can be calculated. There are three commonly used methods to calculate normal returns. The constant mean return model (CMR) is a statistical model that postulates expected returns are simply the mean of returns in the estimation window. Another model is the market model, which calculates expected return by accounting for general market movements. This requires an OLS regression of stock return on the market return. Finally, the capital asset pricing model (CAPM) calculates the expected return by accounting for risk investors bear when buying a specific stock. The market model is more comprehensive than the CMR as the CMR does not control for market movements. Brown and Warner (1985) find that the CMR is mis-specified when there is event clustering. Event clustering occurs when different tweets have overlapping event windows. This is found as Trump often tweets about two different companies on consecutive days. Therefore, the market model is more suitable than the CMR. In addition, Brown and Warner (1980) and MacKinlay (1997) find that the market model is a more powerful test than CAPM for event studies. Therefore, I use the market model to estimate normal returns.

The market model firstly requires an OLS regression:

$$R_{i,t} = \alpha_i + \beta_i R_{S\&P500,t} + \varepsilon_{i,t}$$
$$E(\varepsilon_{i,t}) = 0$$

Where $R_{i,t}$ is the daily return of stock i, α_i is the intercept, β_i is the beta of the stock, and $R_{S\&P500,t}$ is the return of the S&P500 index, which is used as the market proxy. $\varepsilon_{i,t}$ is the error term which has a mean of zero.

The beta and intercept results and the actual daily return of the S&P500 are then used to find the daily normal return for each stock. This daily normal return is subtracted from the stock's actual return to obtain an estimate of abnormal return for stock i on day t.

$$E(R_{i,t}) = \alpha_i + \beta_i R_{S\&P500,t}$$
$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

As Trump tweets about many stocks, the abnormal return of each stock can be combined into a portfolio and averaged. This is the average abnormal return (AAR):

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$$

Where N is the number of stocks.

To test how quickly the market adjusts to new information, the cumulative average abnormal returns (CAAR) must be derived. The cumulative average abnormal return is expressed as one number across different event windows:

$$CAAR_{(T_1,T_2)} = \sum_{t=T_1}^{T_2} AAR_{\mathrm{t}}$$

Where T_1 is the first day in the event window and T_2 is the last day in the event window.

5.1.3. Significance test for AAR & CAAR - Crude Dependence Adjustment (CDA):

Brown and Warner (1980) established the crude dependence adjustment test to check for the significance of AAR and CAAR values. The advantage of this test is that it compensates for dependence of returns across events by estimating the standard deviation of AAR using the estimation window.

The t-statistic is calculated as:

$$t = \frac{AAR_t}{\hat{\sigma}_{AAR}}$$

Where:

$$\hat{\sigma}_{AAR} = \sqrt{\frac{\sum_{t=-271}^{-21}(AAR_t - \overline{AAR})^2}{250}}$$

Where $\hat{\sigma}_{AAR}$ is the standard deviation of average abnormal returns, $t = -271$ to $t = -21$ is the estimation window period and 250 is the number of days in the estimation window. $\overline{AAR}$ is the mean of the average abnormal returns over the estimation window:

$$\overline{AAR} = \frac{\sum_{t=-271}^{-21} AAR_t}{250}$$

The critical value for the market model is calculated with degrees of freedom d-2 where d is the number of days in the estimation window (250 days in this paper).

The test statistic for CAAR is given as:

$$t = \frac{CAAR_t}{(T_2 - T_1 + 1)^{\frac{1}{2}}\,\hat{\sigma}_{AAR}}$$

Where $T_2 - T_1$ is the length of the event window.

5.2. Average Abnormal Trading Volume (AAV)

The mean-adjusted abnormal trading volume is calculated through Microsoft Excel using the formula:

$$AV_{it} = \frac{V_{it} - \bar{V}_i}{\bar{V}_i}$$

Where AV_{it} is change in abnormal trading volume for security i on day t, V_{it} is the trading volume of security i on day t (obtained through Yahoo Finance) and $\bar{V}_i$ is the average trading volume of security i, estimated through the estimation window:

$$\bar{V}_i = \frac{\sum_{t=-271}^{-21} V_{it}}{250}$$

This abnormal trading volume can then be aggregated across stocks into a portfolio and then the AAV can be calculated:

$$AAV_t = \frac{\sum_{i=1}^{N} AV_{it}}{N}$$

Where N is the number of stocks.

5.2.1. Significance Test for Average Abnormal Trading Volume (AAV)

The portfolio test, pioneered by Campbell and Wasley (1996), is used to assess the significance of average abnormal trading volume. The portfolio test statistic is:

$$t = \frac{AAV_t}{\hat{\sigma}_{AAV}}$$

Where $\hat{\sigma}_{AAV}$ is the standard deviation of average abnormal volume and is calculated as:

$$\hat{\sigma}_{AAV} = \sqrt{\frac{\sum_{t=-271}^{-21}(AAV_t - \overline{AAV})^2}{250}}$$

Where $\overline{AAV}$ is the mean of the average abnormal volume over the estimation window:

$$\overline{AAV} = \frac{\sum_{t=-271}^{-21} AAV_t}{250}$$

This test statistic is distributed through a student t distribution with d-1 degrees of freedom, where d is the number of days in the estimation window.

5.3. Google Search Activity

In order to test whether Trump's tweets catch the attention of retail investors, a novel approach established by Born et al. (2017) is incorporated.

Google Trends is used in order to find Google search activity data. Google Trends provides a search index for keywords searched on Google at a particular period of time. A limitation of this method is that Google provides relative search data rather than absolute search data. Google search data is indexed relative to a user-defined period. A period of 30 October, 2016 to 7 February, 2018 is used. This period is used as the first tweet in the sample was made on 11 November, 2016 so we can relate Google search activity on the event date to two weeks before the initial tweet date. The last tweet in the sample was on 24 January, 2018 so the index time range ends on 7 February, 2018 to compare the Google search activity two weeks after the initial tweet. One other limitation is that Google searches are not just used by investors. For instance, Amazon is in the sample of tweets analysed and in the Christmas period, many people use Amazon to shop. As a result, Google search activity for the keyword 'Amazon' will unsurprisingly increase. This is not because of Trump's tweet. To control for this, the search activity of the keyword 'Amazon stock price' is used rather than just 'Amazon' (see appendix D). Google Trends provides weekly data rather than daily data. A value of 100 implies that a particular search term (for instance 'Lockheed Martin stock price') was the most popular search during a certain week in the period between October 2016 to March 2018. As will be shown in the results section, Google search activity is averaged across stocks, in order to find aggregate effects. Some of the 24 tweets used are aimed at the same company. Out of the 24 tweets there are 16 different companies mentioned. For simplicity, the tweets that are considered are the ones that occur the earliest as there is a relative index. For instance, Trump tweets about Ford on 17 November, 2016 and 4 January, 2017. The Google search activity is found for the earlier tweet. This is because if the activity for the later tweet is found, this index would include the effect of the earlier tweet and therefore this would bias the relative search activity value.

5.4. Hypotheses:

To test market efficiency, we first assess whether Trump actually has an effect on financial markets.

$$H_0: AAR = 0$$
$$H_1: AAR \neq 0$$

If the null hypothesis is rejected, it can be argued that Trump does have an impact on financial markets.

After this, the CAAR can be analysed to see how long this effect lasts.

$$H_0: CAAR = 0$$
$$H_1: CAAR \neq 0$$

If this null hypothesis is rejected, market efficiency can be tested by finding how many days this CAAR lasts. Generally, if we find that the CAAR lasts for more than 1 trading day it is argued that markets are inefficient.

To test the attention-based hypothesis, average abnormal trading volume is measured.

$$H_0: AAV = 0$$
$$H_1: AAV \neq 0$$

If the null hypothesis is rejected this means that abnormal trading volume is seen on average across stocks when Trump tweets. Google search activity confirms that it is retail investors acting upon Trump's tweets. If Google search activity increases on the week of Trump's tweet, this implies that Trump draws attention to specific companies and thus drives market inefficiency.

6. Results: Testing the Efficient Market Hypothesis (EMH)

Firstly, the results for the market model coefficients are estimated and then AAR and CAAR are estimated. The results for AAR and CAAR are classified by sentiment to find whether a negative tweet by Trump leads to a negative abnormal return and a positive tweet leads to a positive abnormal return.

6.1. Coefficients from Market Model Regression

Stock	Intercept	Slope
Ford	-0.00102 (-1.30)	1.22 (13.89)
United Technologies	0.00009 (0.189)	0.87 (15.56)
Rexnord	-0.00022 (-0.23)	1.57 (14.18)
Softbank	0.00033 (0.25)	1.16 (7.70)
Boeing	-0.00010 (-0.14)	1.22 (14.84)
Lockheed Martin	0.00073 (1.19)	0.53 (7.73)
General Motors	0.00001 (0.02)	1.06 (11.23)
Toyota	-0.00037 (-0.50)	1.08 (12.63)
Amazon	0.00071 (1.15)	1.02 (9.96)
Comcast	0.00082 (1.68)	0.68 (8.50)
American Airlines	-0.00001 (0.01)	1.62 (8.35)
Facebook	0.00059 (0.98)	1.14 (9.98)
CBS	0.00010 (0.14)	0.68 (4.37)
Wells Fargo	-0.00045 (-0.66)	1.46 (9.20)
Disney	-0.00015 (-0.24)	0.53 (3.80)
J.P. Morgan	-0.0005 (-0.09)	1.46 (12.06)

Table 1: T-statistics are in parentheses. The results are obtained from the OLS market model regression: $R_{i,t} = \alpha_i + \beta_i R_{S\&P500,t} + \varepsilon_{i,t}$

Alpha is the intercept of the regression and beta is the slope. Beta measures the volatility of a stock relative to the market. In other words, it measures market risk. All beta values are statistically significant. The S&P500 index is assigned a beta of 1. A stock with a beta that is higher than 1 means that the stock is more volatile than the market, implying the stock is risky and a beta of less than 1 means the stock is less volatile than the market. For instance, Ford has a beta of 1.22 and therefore Ford is 1.22 times more volatile than the S&P500 index. As a result of this, the regression will show that riskier stocks with higher beta values have higher expected returns as the market compensates higher risk.

6.2. Average Abnormal Returns (AAR) Results

AAR: Positive Tweets	All positive tweets (n = 24)			Positive tweets, excluding response tweets and tweets near earnings (n=8)		
	(1)			(2)		
Event time	AAR	t-statistic	p-value	AAR	t-statistic	p-value
-10	0.02%	0.09	0.93	0.43%	0.98	0.33
-9	0.32%	1.15	0.25	0.72%	1.63	0.10
-8	0.49%	1.78	0.08	-0.14%	-0.31	0.76
-7	-0.09%	-0.33	0.74	-0.66%	-1.48	0.14
-6	-0.34%	-1.22	0.22	-0.42%	-0.94	0.35
-5	0.11%	0.39	0.70	-0.04%	-0.08	0.94
-4	0.50%	1.81	0.07	0.24%	0.53	0.59
-3	0.31%	1.11	0.27	-0.58%	-1.31	0.19
-2	-0.05%	-0.19	0.85	0.25%	0.57	0.57
-1	0.26%	0.93	0.35	0.61%	1.38	0.17
0	0.50%	1.81	0.07	1.04%***	2.36	0.02
1	0.41%	1.46	0.14	0.35%	0.80	0.42
2	0.12%	0.42	0.67	0.24%	0.55	0.58
3	-1.26%****	-4.53	0.00	-0.37%	-0.83	0.40
4	-0.42%	-1.51	0.13	0.17%	0.38	0.70
5	0.03%	0.10	0.92	-0.17%	-0.38	0.71
6	0.20%	0.73	0.47	0.32%	0.72	0.47
7	0.16%	0.57	0.57	0.48%	1.08	0.28
8	-0.05%	-0.19	0.85	0.06%	0.13	0.90
9	0.32%	1.14	0.26	0.38%	0.85	0.39
10	0.13%	0.45	0.65	0.37%	0.83	0.41

Table 2: AAR Positive Tweets ****significant at 1% level, ***significant at 2% level

Column (1) in table 2 shows that for a sample of all 24 positive tweets, there is a small positive abnormal return on the day of the tweet of 0.50%. This is statistically insignificant and therefore it may be inferred that a positive tweet by Trump has no effect on the market. Interestingly, there is a significant negative effect on day 3. This may be because some earnings announcements happen after Trump's tweet, leading to a change in the stock price. This is confirmed in Column (2) which shows the average abnormal returns for the subsample of positive tweets that do not occur in proximity to earnings announcements and are not response tweets. This is the actual subsample used to test the EMH. A significant negative effect is no longer seen on day 3. On the day of a positive Trump tweet, there is an average abnormal return of 1.04%. This is statistically significant at the 2% level. This provides evidence to reject the null hypothesis that a positive tweet by Trump has no effect on returns of individual stocks.

AAR: Negative Tweets	All negative tweets (n=20)			Negative tweets, excluding response tweets and tweets near earnings (n=16)		
	(1)			(2)		
Event time	AAR	t-statistic	p-value	AAR	t-statistic	p-value
-10	-0.15%	-0.52	0.60	-0.11%	-0.38	0.70
-9	-0.22%	-0.77	0.44	-0.23%	-0.78	0.43
-8	-0.10%	-0.35	0.72	0.14%	0.49	0.62
-7	0.02%	0.07	0.94	-0.12%	-0.41	0.68
-6	-0.09%	-0.33	0.74	-0.08%	-0.28	0.78
-5	-0.32%	-1.12	0.26	-0.22%	-0.77	0.44
-4	-0.29%	-1.02	0.31	-0.29%	-1.00	0.32
-3	0.07%	0.24	0.81	0.28%	0.98	0.33
-2	-0.31%	-1.11	0.27	-0.28%	-0.96	0.34
-1	-0.22%	-0.77	0.44	-0.21%	-0.72	0.47
0	-0.31%	-1.11	0.27	-0.85%****	-2.93	0.00
1	0.03%	0.10	0.92	-0.20%	-0.67	0.50
2	0.20%	0.71	0.48	0.21%	0.71	0.48
3	-0.17%	-0.60	0.06	-0.56%	-1.93	0.06
4	0.40%	1.43	0.15	0.46%	1.59	0.11
5	-0.12%	-0.41	0.68	-0.02%	-0.05	0.96
6	-0.05%	-0.19	0.85	0.30%	1.03	0.30
7	-0.02%	-0.06	0.95	-0.17%	-0.59	0.55
8	-0.21%	-0.73	0.46	-0.38%	-1.32	0.19
9	0.18%	0.65	0.51	0.19%	0.65	0.52
10	-0.07%	-0.24	0.81	0.21%	0.72	0.47

Table 3: AAR Negative Tweets ****significant at 1% level

Column (1) in table 3 shows the average abnormal returns for all 20 negative Trump tweets in the sample. The results show that on the day of a negative Trump tweet, a small negative abnormal return of -0.31% is found. This is statistically insignificant and therefore it may be inferred that a negative tweet by Trump has no effect on the market. However, this sample contains tweets that are responses or are posted near earnings announcements and therefore this may lead to misinterpretation of the impact of Trump's tweets on abnormal returns. Using a subsample of 16 negative tweets that are not posted near earnings announcements and are not response tweets, the results in column (2) show that there is a negative effect on the day of Trump's tweet of -0.85%. This is statistically significant at the 1% level. This provides evidence to reject the null hypothesis that a negative Trump tweet does not impact the returns of individual stocks.

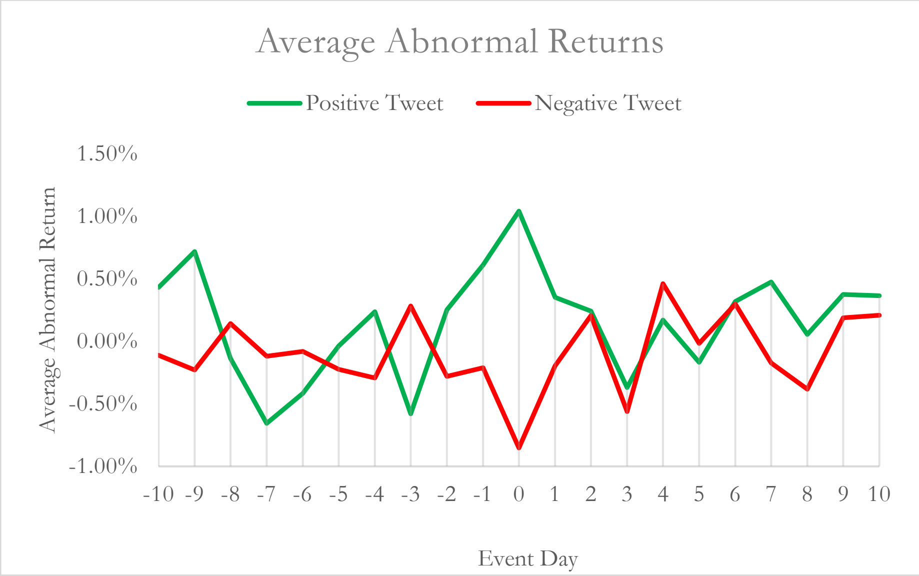

Figure 3: Average abnormal returns for positive and negative tweets

Figure 3 shows that that for positive tweets, on event day 0, there is a spike in abnormal returns of 1%. For negative tweets there is a negative spike down to -0.85%. Interestingly, on day 2, AARs return to pre-event levels. This suggests that the markets takes 2 days to adjust to new information and therefore is inefficient. This will be analysed formally through CAAR.

Overall, the AAR results show that the null hypothesis of no impact of Trump's tweets on AAR can be rejected. As a result, the EMH can be tested by analysing the CAAR.

6.3. Cumulative Average Abnormal Return (CAAR)

CAAR: Negative & Positive Tweets	Negative tweets, excluding response tweets and tweets near earnings (n=16)			Positive tweets, excluding response tweets and tweets near earnings (n=8)		
	(1)			(2)		
Event window	CAAR	t-statistic	p-value	CAAR	t-statistic	p-value
(-10,-1)	-1.12%	-1.22	0.22	0.43%	0.31	0.76
(0,1)	-1.05%***	-2.55	0.01	1.40%**	2.23	0.03
(0,2)	-0.84%*	-1.67	0.05	1.64%**	2.14	0.03
(0,3)	-1.40%***	-2.41	0.02	1.27%	1.44	0.15
(0,4)	-0.94%	-1.45	0.15	1.44%	1.46	0.15
(0,5)	-0.96%	-1.34	0.18	1.27%	1.18	0.24
(-10,10)	-1.93%	-1.45	0.15	3.30%	1.63	0.10

Table 4: ***Significant at 2% level, **Significant at 5% level, *Significant at 10% level

Column (1) in table 4 shows the CAAR of a subsample of 16 negative tweets that do not include responses or earnings. There is a CAAR of -1.12% in the (-10,-1) pre-event period but this is statistically insignificant which means that results are not contaminated by preceding events. Looking across the whole 21-day sample, we find that there is a negative impact of -1.93% but this is statistically insignificant so there seems to be no long-term impact of Trump's tweets. The immediate impact of a negative tweet is a negative return on average across stocks. This is shown by the event window (0,1). There is an impact of -1.05% on average across the day of the tweet and the day after the tweet. This is statistically significant at the 2% level. There is a significant weaker negative effect of -0.84% for the (0,2) event window. Interestingly, the (0,3) event window CAAR shows that there is a stronger negative effect of -1.40%, 3 trading days after the tweet is made and this is statistically significant at the 2% level. A possible reason for this is that Donald Trump's tweets are released by the media a couple of days after he tweets, therefore the effect may be delayed. Four trading days after the tweet, there is no longer an effect of Trump's tweets as the CAARs are no longer statistically significant. This means that the market has adjusted. This is inconsistent with the semi-strong form of EMH, as new information is not incorporated rapidly into the market.

Column (2) shows the results for a subsample of 8 positive tweets that are not response tweets and do not occur near earnings announcements. There is a CAAR of 0.43% in the pre-tweet period but this is statistically insignificant. Similarly to negative Trump tweets, there is no long-term impact on the market. There is an significant immediate impact of 1.40% for the (0,1) event window. Looking at the (0,2) event window, there is a stronger positive effect of 1.64% which is statistically significant at the 5% level. The (0,3) event window shows that there is a positive effect 3 trading days after the tweet is made but this is not statistically significant. Unlike negative Trump tweets, on day 3, there is not a strong effect. This may contradict the initial suggestion that the media is delayed in releasing information about Trump tweets. However, usually the media only highlight negative Trump content. Therefore, this abides by the results, as negative Trump tweets would receive more media coverage whereas positive tweets would not.[10]

Overall, the CAARs for both positive and negative tweets provide enough evidence to reject the null hypothesis that markets are efficient as the market does not incorporate new information instantly.

[10] Pew Research Centre finds that 62% of media coverage on Trump is negative and only 5% is positive. Therefore, it may be argued that only negative tweets receive media coverage and positive tweets do not. This is why we see a stronger effect on day 3 for negative tweets relative to positive tweets.

7. Results: Testing for Attention-Based Investing

7.1. Average Abnormal Trading Volume (AAV) Results

AAV: Positive & Negative Tweets	Positive & Negative tweets, excluding response tweets and tweets near earnings (n = 24)		
	(1)		
Event time	AAV	t-statistic	p-value
-5	-9.11%	-0.64	0.53
-4	-1.72%	-0.12	0.90
-3	-8.78%	-0.61	0.54
-2	-10.49%	-0.73	0.46
-1	21.80%	1.52	0.13
0	43.57%****	3.04	0.00
1	17.29%	1.21	0.23
2	-10.39%	-0.73	0.47
3	-5.40%	-0.38	0.71
4	8.52%	0.59	0.55
5	6.06%	0.42	0.67

Table 5: T-statistics are in parentheses. ****Significant at 1% level

A subsample of 8 positive and 16 negative tweets that do not occur near earnings announcements and are not response tweets are used. Table 5 shows that on day 0, there is a spike in abnormal trading volume of 43.57%. This is statistically significant at the 1% level. However, after day 0, abnormal trading volumes are statistically insignificant. This implies that Trump's tweets do generate investor attention. Findings are consistent with the attention-based investing hypothesis if retail investors act upon the information and Google search activity confirms this.

7.2. Google Search Activity:

Company	Week -2	Week -1	Week 0	Week +1	Week +2
Ford	42	49	52	47	44
United Technologies	36	29	100	77	54
Rexnord	0	0	100	97	0
Softbank	0	8	60	23	8
Boeing	46	24	16	16	16
Lockheed Martin	36	35	100	71	24
General Motors	22	23	85	53	27
Toyota	38	39	100	63	50
Amazon	52	46	32	29	33
Comcast	40	59	69	46	58
American Airlines	23	9	14	11	9
Facebook	53	52	61	65	53
CBS	63	56	95	69	94
Wells Fargo	45	53	59	49	43
Disney	68	56	53	47	41
J.P. Morgan	49	37	87	79	74
Average	**38**	**36**	**68**	**53**	**53**

Table 6: These values are the relative number of searches for each company during the period October 2016 to February 2018

On the week of the tweet, Google Trends finds that Trump's tweets lead to an increase in the search volume index from 36 in the previous week to 68 on average. A week after the event week, the Google search activity begins to fall. This is consistent with attention-based buying as investors only draw attention to stocks mentioned by Trump for the event week. After this, investor attention is diverted away from these stocks.

8. Discussion:

8.1. General Analysis

This study finds that Trump can affect financial markets with his tweets. The effect of a positive and negative tweet on abnormal returns is statistically and economically significant as the effect on returns usually follows the sentiment of the tweet (a positive tweet leads to positive abnormal returns). Interestingly, a positive tweet by Trump has more of an effect than a negative tweet on the market. This contrasts from Ge et al. (2017) who find no difference in the effect of a negative and positive tweet. A possible reason for this is that Trump's company-specific tweets are usually very negative and therefore positive tweets about companies are unexpected and therefore lead to higher returns. Another reason for this may be that the positive tweet subsample is smaller than the negative tweet subsample and therefore this may limit interpretation. The market generally takes 2 to 3 trading days to incorporate the information contained in these tweets and therefore the findings are inconsistent with the semi-strong form of EMH. This is in line with studies by Born et al. (2017) and Ge et al. (2017). A key contribution of this study is attention-based investing. Retail investors in particular tend to focus on stocks mentioned by Trump and therefore do not consider all available information. Contrastingly, Born et al. (2017) finds noise trading as the reason for market inefficiencies, whereas Ge et al. (2017) do not provide a reason for observed market inefficiencies.

A real-world implication of this study is that trading strategies can be devised so that when Trump tweets positively (negatively) an investor can short (buy) the stock and then exit their position after 2 or 3 trading days. However, this may depend upon broker or transaction costs as abnormal returns may not be high enough to cover this. Therefore, retail investors may not be able to devise profitable strategies based upon Trump's tweets. Nonetheless, institutional investors, who can benefit from lower transaction costs, may be able to profit from these announcements and devise trading strategies.

8.2. Justifications

EMH states that it is impossible to beat the market if markets are efficient. This event study shows that the markets are possible to beat. However, if transaction costs are incorporated, there may be a possibility that markets are actually efficient as the abnormal returns seen are low. Nevertheless, there are now many brokers that charge various commissions. For instance, some brokers offer flat rates per trade whereas others charge a monthly rate. Statistics for average transaction costs in the US are difficult to obtain and therefore, it is unclear how to include transaction costs into an event study. As a result, similar to other event studies[11], transaction costs are disregarded and focus is kept on the informational efficiency of markets.

8.3. Limitations

The small sample size for positive tweets limits interpretation. This is because most positive tweets by Trump are response tweets, simply thanking companies for abiding by his policies. The sample size in this study is 24 and this is an enlargement of previous work on the impact of Trump's tweets on financial markets. However, a larger sample size would improve this analysis. Additionally, it could be argued that Google search activity is limited in its interpretation as the data is indexed and is found on a weekly basis. On the other hand, this paper incorporates trading volume in order to complement the result of Google Search Activity. A possible limitation of event studies is that some preceding events may not be accounted for. However, to minimise this limitation, this study excludes tweets that occur during earnings and company announcements. This reduces the chance that preceding events drive the impact of Trump's tweets.

9. Conclusion

This paper finds that positive and negative Trump tweets move stock prices and lead to significant abnormal returns. These effects last 2-3 trading days, which implies that the market is inefficient. These findings suggest that Donald Trump does indeed use Twitter as a strategic tool to influence the stock price and hence the actions of target companies. A key strength of this paper is the new insight it adds in the form of attention-based buying. Transitory increases in trading volume and Google search activity implies that Trump catches the attention of retail investors who do not consider all available information.

Future research could innovate a way of incorporating transaction costs to make results more robust and devise profitable trading strategies for retail and institutional investors. In order to

[11] All studies mentioned in the literature review disregard transaction costs including Ge et al. (2017) and Born et al. (2017).

increase the accuracy of results, researchers could increase the sample size by analysing tweets at the end of Trump's presidential term. This would provide results that are more reliable. A bigger sample size also means that specific industries could be analysed. For instance, some industries that rely heavily on government contracts (such as defence) may be more susceptible to Trump's tweets. Furthermore, as Twitter rises in popularity, the effect of celebrities and other politicians on financial markets could be analysed. Recently, Kylie Jenner tweeted negatively about Snap Co. and this lead to a decrease in its stock market value by £1 billion. This shows that with a large follower base, celebrities and politicians can affect organisations for the better or the worse. As result, regulators may want to consider scrutinising the effect of Twitter on financial markets more critically in the future.

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11. Appendices

11.1. Appendix A: Summary of Literature

Paper	Announcement type	Time range	How long does the post-announcement effect last?	Is the market efficient?	Sample size
Fama, Fisher, Jensen and Roll (1969)	Stock splits	1927-1959	0 months	Yes	940 stock splits
Ball and Brown (1968)	Annual earnings announcements	1944-1966	6 months	No	75 firms
Bernard and Thomas (1989)	Quarterly earnings announcements	1974-1986	60 days	No	84,792 firm-quarters of data
Charest (1978)	Dividend policy	1947-1967	3 months	No	1720 dividend announcements
Tetlock (2007)	Newspaper column	1984-1999	2 days	No	30 firms
Ranco et al. (2015)	Tweets	2013-2014	10 days	No	100,000 tweets
Malaver and Vojvodic (2017)	Trump's tweets	2015-2017	N/A	N/A	7,429 tweets
Born et al. (2017)	Trump's tweets	2016	5 trading days	No	15 tweets
Ge et al. (2017)	Trump's tweets	2016-2017	2 trading days	No	48 tweets – 18 of which are informative

11.2. Appendix B: Earnings Announcement Dates

Earnings Dates 2017	Q4 2016	Q1 2017	Q2 2017	Q3 2017	Q4 2017	Q1 2018
Ford	**01/26/2017**	04/27/2017	07/26/2017	10/26/2017	24/01/2018	04/25/2018
General Motors	02/07/2017	04/28/2017	07/25/2017	10/24/2017	02/06/2018	04/26/2018
Toyota	02/06/2017	05/10/2017	08/04/2017	11/07/2017	02/06/2018	05/09/2018
Fiat Chrysler	01/26/2017	04/26/2017	07/27/2017	10/24/2017	**01/25/2018**	04/26/2018
Walmart	02/21/2017	05/17/2017	08/17/2017	11/16/2017	02/20/2018	05/17/2018
Intel	01/26/2017	04/27/2017	07/27/2017	10/26/2017	01/25/2018	04/26/2018
Nordstrom	02/23/2017	05/11/2017	08/10/2017	11/09/2017	03/01/2018	05/10/2018
Exxon	01/31/2017	04/28/2017	07/28/2017	10/27/2017	02/02/2018	04/27/2018
Rexnord	02/02/2017	05/18/2017	08/02/2017	11/01/2017	01/31/2018	05/16/2018
Amazon	02/02/2017	04/27/2017	07/27/2017	10/26/2017	02/01/2018	04/26/2018
Comcast	01/26/2017	04/27/2017	07/27/2017	10/26/2017	01/24/2018	04/25/2018
Corning	01/24/2017	04/25/2017	07/26/2017	10/24/2017	01/30/2018	04/24/2018
Merck	02/02/2017	05/02/2017	**07/28/2017**	10/27/2017	02/02/2018	05/01/2018
Pfizer	01/31/2017	05/02/2017	08/01/2017	10/31/2017	01/30/2018	05/01/2018
CBS	02/15/2017	05/04/2017	**08/07/2017**	11/02/2017	02/15/2018	05/03/2018
American Airlines	01/27/2016	04/27/2017	07/28/2017	10/26/2017	01/25/2018	04/26/2018
Facebook	02/03/2017	05/03/2017	07/26/2017	11/01/2017	01/31/2018	05/02/2018
Broadcom	12/08/2016	03/01/2017	06/01/2017	08/24/2017	12/06/2017	03/15/2018
Wells Fargo	01/13/2017	04/13/2017	06/14/2017	10/13/2017	01/12/2018	03/08/2018
Apple	10/21/2016	01/31/2017	05/02/2017	08/01/2017	11/02/2017	02/01/2018
Disney	11/10/2016	02/07/2017	05/09/2017	08/08/2017	11/09/2017	02/06/2018
J.P. Morgan	01/13/2017	04/13/2017	07/14/2017	10/12/2017	01/12/2018	04/12/2018

These dates are used in order to determine whether Trump's tweets occur during earnings announcements. The bolded dates highlight earnings announcements that occur in proximity to Trump's tweets.

11.3. Appendix C: Positive and Negative Tweets

Positive Tweets Sample:

Company	Ticker	Date	Time	Does The Tweet Occur Near Earnings Date?	Is The Tweet A Response To A Company Announcement?	Subject Of The Tweet
Ford	F	11/17/2016	9:51 PM	No	No	Announcing that Ford are keeping plant in US not Mexico
United Technologies	UTC	11/24/2016	10:12 AM	No	No	Working on Carrier to stay in US
United Technologies*	UTC	11/29/2016	10: 40 PM	No	Yes	Responding to UTC staying in US
Softbank	SFTBK	12/06/2016	2:10 PM	No	No	Announcing Softbank CEO agreeing to invest in US
Boeing	BOE	12/22/2016	5:26 PM	No	No	Asked BOE to price out LMT
Ford	F	01/04/2017	8:19 AM	No	No	Announcing ford scrapping new plant in Mexico
Fiat Chrysler*	FCAU	01/09/2017	9:14 AM	No	Yes	Responding to FCAU investment
General Motors*	GM	01/17/2017	12:55 PM	No	Yes	Thank you for investment
Walmart*	WMT	01/17/2017	12:55 PM	No	Yes	Thank you for investment
General Motors*	GM	01/24/2017	7:47 PM	No	Yes	Great meeting with CEO
Ford*	F	01/24/2017	7:47 PM	Yes	Yes	Great meeting with CEO
Intel*	INTC	02/08/2017	2:22 PM	No	Yes	Thank you for investment
Exxon*	XOM	03/06/2017	4:19 PM	No	Yes	Thank you for investment
Corning*	GLW	07/21/2017	10:31 PM	No	Yes	Thank you for investment & new jobs
Merck*	MRK	07/21/2017	10:31 PM	No	Yes	Thank you for investment & new jobs
Pfizer*	PFE	07/21/2017	10:31 PM	No	Yes	Thank you for investment & new jobs
American Airlines	AAL	09/22/2017	12:54 PM	No	No	Helping with flights during the hurricane
Broadcom**	AVGO	11/02/2017	2:58 PM	No	Yes	Thank you for investment
Toyota*	TM	01/10/2018	6:37 PM	No	Yes	Thank you for investment and new jobs

Apple*	AAPL	01/17/2018	06:28 PM	No	Yes	Thank you for investment and new jobs
Fiat Chrysler*	FCAU	01/17/2018	6:32 PM	No	Yes	Thank you for moving from Mexico to US
Disney	DIS	01/24/2018	6:58 AM	No	No	Good progress in US
J.P. Morgan	JPM	01/24/2018	6:58 AM	No	No	Good progress in US
Fiat Chrysler*	FCAU	01/28/2018	8:18 AM	Yes	Yes	Thank you for moving from Mexico to US

*Excluded tweets as they either are response tweets or occur near earnings announcements
**Broadcom announced bid for Qualcomm and this tweet is excluded as a result

Negative tweets sample:

Company	Ticker	Date	Time	Does The Tweet Occur Near Earnings Date?	Is The Tweet A Response To A Company Announcement?	Subject Of The Tweet
Rexnord	RXN	12/02/2016	10:06 PM	No	No	Worker negligence
Boeing	BOE	12/06/2016	8:52 AM	No	No	Boeing prices are out of control
Lockheed Martin	LMT	12/12/2016	2:26 PM	No	No	F-35 programme out of control
Lockheed Martin	LMT	12/22/2016	5:26 PM	No	No	Asked Boeing To Price out LMT
General Motors	GM	01/03/2017	7:30 AM	No	No	Threating large border taxes
Toyota	TM	01/05/2017	1:14 PM	No	No	Threating large border taxes
Nordstrom*	JWN	02/08/2017	10:51 AM	No	Yes	Frustration at Nordstrom discontinuing Ivanka Trump's clothing line
Rexnord	RXN	05/07/2017	5:58 PM	No	No	Threatening to tax products sold in us
Amazon	AMZ	06/28/2017	8:06 AM	No	No	Amazon should pay internet taxes
Comcast	CMCSA	07/01/2017	7:59 AM	No	No	Fake news
CBS*	CBS	08/07/2017	6:18 AM	Yes	No	Fake news
Merck*	MRK	08/14/2017	7:54 AM	Yes	No	'Rip-off' drug prices
Amazon	AMZ	08/16/2017	5:12 AM	No	No	Amazon damaging tax-paying retailers
Facebook	FB	09/27/2017	8:36 AM	No	No	Suggesting collusion between FB and CBS
CBS	CBS	10/17/2017	4:51 PM	No	No	Fake news
Facebook	FB	10/21/2017	3:06 PM	No	No	Fake news
CBS	CBS	10/21/2017	3:06 PM	No	No	Fake news
Comcast*	CMCSA	11/29/2017	7:16 AM	No	Yes	Fake news
Wells Fargo	WF	12/08/2017	10:18 AM	No	No	Threating tougher penalties for behaviour
Amazon	AMZ	12/29/2017	8:04 AM	No	No	Amazon should pay more to US Post Office

*Excluded tweets as they either are response tweets or occur near earnings announcements

11.4. Appendix D: Google Search Terms

Company	Ticker	Search Term Used
Ford	F	'Ford stock price'
United Technologies	UTC	'United Technologies stock price'
Rexnord*	RXN	'Rexnord stock'
Softbank	SFTBK	'Softbank stock price'
Boeing	BOE	'Boeing stock price'
Lockheed Martin	LMT	'Lockheed Martin stock price'
General Motors	GM	'General Motors stock price'
Toyota	TM	'Toyota stock price'
Amazon	AMZ	'Amazon stock price'
Comcast	CMCSA	'Comcast stock price'
American Airlines	AA	'American Airlines stock price'
Facebook	FB	'Facebook stock price'
CBS	CBS	'CBS stock price'
Wells Fargo	WF	'Wells Fargo stock price'
Disney	DIS	'Disney stock price'
J.P. Morgan	JPM	'JP Morgan stock price'

*'Rexnord stock' is used as the search term instead of 'Rexnord stock price' as there were not enough searches for Rexnord stock price