

Trump and Twitter

What Impact do Trump Tweets have on Share Prices of Targeted Firms

Master Thesis

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Chapter 1: Introduction

President Donald J. Trump is one of the hottest topics on the globe right now. After his unexpected win in the United States' election last November, Donald Trump has dominated headlines around the world. It is almost impossible to turn on the news without Trump being mentioned at least once. His unorthodox ways regarding governing and handling of the media has led to worldwide shock and uncertainty as to what lies ahead.

The shock of the election's unexpected outcome also sent a shockwave through the scientific community. A majority of trusted polls had indicated that Hillary Clinton was going to win the election with a high degree of certainty. On election day, the New York Times even predicted with 96% certainty that Secretary Clinton would be elected 45th President of the United States.

President Trump is unique in a sense that his actions and behaviour deviate substantially from the way Presidents normally behave and how the world expects American Presidents to behave. His volatile personality and distrust of the mainstream media could potentially be a toxic mix.

One of the most controversial aspects of Trump's Presidency up until now is the use of his Twitter account and its consequences. During the campaign, Trump frequently used the medium to attack his opponents and permeate his message and views, unfiltered. At that time, his tweets were generally received with a lot of criticism due to their harsh nature and tone. This tone was expected to be more moderate and graceful after the election, as the weight of the Presidency and its responsibilities would have sunk in.

That assumption would be proven wrong almost immediately and Mr. Trump would frequently use Twitter to vent his anger and opinions. The main difference now was that the 140 characters in his tweets would now be backed up by the full force and power of the United States' government.

President Trump frequently mentions companies and corporations in his tweets, which according to news outlets causes their share prices to drop dramatically. Take for instance the tweet in which Trump mentions that he thinks that the cost of the Joint Strikefighter F-35 is spiralling out of control. The impulsive tweet caused Lockheed Martin Corp.'s share price to immediately drop by 4%. This effectively wiped out \$4 billion dollar in market capitalisation.

Considering that a tweet only has 140 characters, the damage to Lockheed Martin in this case amounts to \$28 million per character. Due to this mayhem, there are now apps and websites with the capability to notify you if President Trump is tweeting about a stock you have invested in.

This thesis aims to investigate and answer whether the tweets targeted at companies do any real harm to the return of those companies' stocks.

Current state of literature

The current state of academic literature regarding the subject directly are scarce. The time Trump has dominated the headlines is relatively short and most of what is written about the topic is produced by the major (financial) news outlets. The difference between what is produced by major financial news outlets and this thesis is that this thesis will use event study methodology over different time intervals to draw conclusions. Indirectly, the subject has been on the rise as a hot and interesting topic. Collecting data from social networks has fallen under increased interest by researchers since its use has exploded in combination with the availability of big data (Nettleton, 2011).

Most people have a tendency to overreact to bad news and dramatic events. De Bondt and Thaler (1985) conclude that this overreaction is also exhibited when considering stock returns. It will be interesting to see if the same conclusion holds for reactions following a Trump twee.

Multiple articles have been produced that examine the effects of tweets on the stock market. Zang, Fuehres and Gloor (2011) found that emotions on Twitter play a significant role in predicting stock market behaviour in the short term. To substantiate this claim even further, another study found that the rates at which tweets are created about a particular subject could outperform market predictions regarding returns (Asur and Huberman, 2010). Because of this, it is no surprise that there is a correlation between activity on social media, which is increasing at an ever faster pace, and stock volatility (Antweiler and Frank, 2004). The previously mentioned topics should pivot around event study methodology in this thesis. Event study methodology has been around for decades and a lot of academic texts have been written about it. For finance, this revolves around subjects as acquisitions, mergers, stock splits or major economic announcements. Although event studies have been adopted by multiple disciplines, its most successful applications can be found in finance (Craig

Mackinlay, 1997). In the same paper, Craig Mackinlay also describes multiple variations of how event study research should be conducted and the paper is very similar to the event study methodology paper by de Goeij and de Jong (2011). A combination of these articles will be the blueprint on which the theoretical framework of this paper will be constructed.

Main research question

The volatile behaviour of Trump in combination with the power of the office of the U.S. Presidency is the basis of this thesis. The central question in this research will be to try and answer how Trump's tweets affect stock prices of the targeted firms. I will look at multiple instances of the main question. For example, what are the immediate short term effects of a negative mention on share prices versus how do the share prices hold up or recover.

I propose to divide the main research question in four subcomponents. Firstly, since Trump has tweeted almost 35.000 tweets since he joined twitter, I'd like to examine the effects of his tweets prior to him running for President. Because his wealth and influence is very substantial, it is interesting to see how his tweets demonstrate his financial power and influence on share prices of targeted companies before his announced Presidential bid.

Secondly, I want to look at the period after he announced his candidacy and see the reaction of the market whenever he tweeted in this period. Quite interesting to research if the markets took Mr. Trump's bid more seriously than the mainstream media and the polls did. A statistically significant negative return would substantiate such a claim.

Thirdly, my research will focus on event studies with tweets that are posted after his win last November. It was expected that his tone would moderate on Twitter after his win, but that expectation was proven wrong, so I'm interested in the market reaction following that. The next and final part will be to combine the three periods and see the tweets' overall impact.

Research Plan Summary

To research the topics in this thesis, I propose to use event study methodology to measure the impact on firms' share prices. This method of research should be relevant assuming the market is rational and thus reflect the events' impact (Craig Mackinlay, 1997), in this case tweets, on the share price.

For event studies, the first step would be to identify the specific event. In this thesis, the event will be a tweet of Trump, targeting a company in the negative sense. I will briefly summarise my plan.

I will need to find abnormal market returns per company, per period, and subtract the return in the estimation window (the benchmark return) from the return in the event window. This so called estimation window will be the control period of the study.

Considering which model to use to estimate the benchmark, I will use the market adjusted returns model in combination with the CAPM. This is to eliminate market wide movements that could influence the abnormal returns.

For every four subcomponents of the study, abnormal returns will be summed and averaged so they can be more informative when looking at deviations from zero, pinpointing to irregular behaviour. Effects unconnected to the event would be neutralized this way (Corrado 2011).

After the abnormal returns for every period have been calculated, t-tests will be conducted to test for statistical significance in the returns, indicating that perhaps the tweets have an effect on the valuation of the stocks.

The results of this study can be summed up as follows: I find that for the citizen and candidate period, there is on average no significant effect that causes stock price depreciation due to Trump Tweets. For these periods, individual fluctuations in price can be mostly attributed to external events on which Mr. Trump responds afterwards on Twitter. For the presidential period however, there is a significant negative statistical effect of the Tweets in the short term only and prices do recover within days of the tweet, perhaps viewed as an empty or hollow threat. I argue that this depreciation in stock price is the result of a direct threat or call to action issued with the tweet, causing stock prices of targeted companies to fall.

Chapter 2: Event Study Methodology

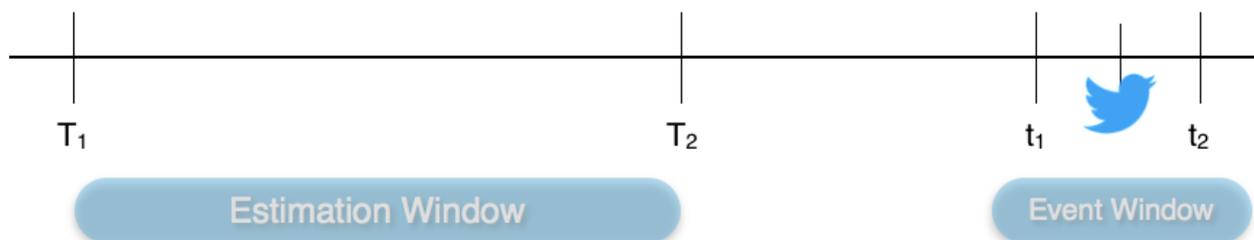
Introduction

Event studies aim to test the significance of a particular event on a firm's stock. The underlying assumption is that, when there are efficient markets where a firm's stocks are traded on, the impact of those events can be measured by the change in a firm's share price around the date of the particular event (De Goeij & De Jong, 2011). The main steps of an event study are first to classify the event of interest, and to specify the period that will be used to investigate the stock price fluctuation of firms in the sample. After that, a model needs to be defined that will predict normal stock returns over a control period, the so called estimation period. With this predicted normal return, it will be possible to check whether the actual return was substantially different from the predicted return during and around the event. This yields an abnormal return that might be caused by the event, in this instance, a tweet by Donald Trump.

Modelling Abnormal Returns

The timeline surrounding the event is depicted in figure 1. T_1 denotes the start of the estimation period and runs up to T_2 . The event window is denoted by t_1, t_2 . The normal return will be estimated in the estimation window and this will be subtracted from the actual return to calculate the abnormal return. The formula for the abnormal returns is as denoted by formula 1.

fig. 1



Where R_{it} denotes the return of firm i at time t and NR_{it} denotes the normal return of firm i at time t .

$$(1) \quad AR_{it} = R_{it} - NR_{it}$$

The estimation period in this study will amount 90 days, starting at 120 trading days prior to the event and ending 30 trading days prior to the event. This approach is similar to the one used by Craig Mackinlay (1997). There will be two different event windows, one that will start at 10 trading days prior and end 10 trading days after the event to capture the cumulative effect of the tweets, and one that will start 1 trading prior to the event and 1 trading day after to look at immediate effects of the tweets. The normal returns NR_{it} , will be calculated using the market model (formula 2).

$$(2) \quad R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$$

NR_{it} is defined by formula 3 where α and β denote the ordinary least squares regression coefficients. Abnormal returns are then defined as the disturbance term in this regression model.

$$(3) \quad NR_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt}$$

Using the market model increases accuracy when predicting the abnormal returns because it adjusts for overall market fluctuations in the market and does not assume, like the market adjusted returns model does, that the beta's of stocks are equal to one, which could bias the results.

Analysis of abnormal returns

After the normal returns have been estimated and abnormal returns calculated, a matrix can be constructed comprised of the abnormal returns that contains all abnormal returns per company from t_1 up until t_2 for the different event windows (4).

$$(4) \quad \begin{bmatrix} AR_{it_1} & \cdots & AR_{Nt_1} \\ \vdots & \ddots & \vdots \\ AR_{it_2} & \cdots & AR_{Nt_2} \end{bmatrix}$$

In this particular example, the rows in this matrix denote the cross-sectional abnormal returns at time t . The columns denote abnormal returns per firm i at a particular time in the event window.

So for this study, two matrices will be constructed; one with an event window spanning 21 days and one with an event window that spans 3 days.

The analysis of abnormal stock returns will be divided in two parts. First, average abnormal returns, that is the mean of the cross-sectional average abnormal return at a time period t (5), will be calculated and tested for significance. This is the mean of a row in the abnormal return matrix. It gives insight in how all of the firms combined at a specific time t react to the tweets. If the average abnormal returns are substantially different from zero, that could indicate extraordinary performance of the stock.

$$(5) \quad AAR_t = \frac{1}{N} \sum_{i=1}^N AR_{it}$$

Second, to test how individual firms perform in the event period, abnormal returns are summed per firm at time t . This will yield the cumulative abnormal return per firm i , or CAR_i . (6)

$$(6) \quad CAR_i = AR_{it_1} + \dots + AR_{it_2} = \sum_{t=t_1}^{t_2} AR_{it}$$

Cumulative average abnormal returns (CAAR's) can also be informative in that they give a cross sectional average of all abnormal returns. This can be constructed by either summing up average abnormal returns or taking the mean of the cumulative abnormal returns (7 & 8).

$$(7 \& 8) \quad CAAR = \sum_{t=t_1}^{t_2} AAR_t \quad CAAR = \frac{1}{N} \sum_{i=1}^N CAR_i$$

Testing abnormal returns

To test whether the observed returns deviate substantially from zero, I begin by defining a basic null hypothesis. (9)

$$(9) \quad H_0: E(AR_{it}) = 0$$

Since it is not particularly informative to check whether an abnormal return is different from zero at one instance of time for an individual firm in the event window, average abnormal returns across all firms in the sample will be checked at a specific point in time in the event window. The null hypothesis will be modified accordingly. (10)

$$(10) \quad H_0: E(AAR_t) = 0$$

This will give an indication if the abnormal returns from firms in the sample are significantly different from zero as to indicate that tweets effect the stock return.

The next step would be to check if the cumulative abnormal returns of the individual firms are different from zero. This gives insight as to whether a particular firm is harmed or affected by a tweet over the whole of the event period. The null hypothesis to be checked for every individual firm is as follows: (11)

$$(11) \quad H_0: E(CAR_i) = 0$$

The final null hypothesis to be constructed is one that deals with the cumulative average abnormal returns. A substantial deviation from zero would indicate that in general, firms are affected by negative tweets. (12)

$$(12) \quad H_0: E(CAAR) = 0$$

To test whether the results from the null hypothesis are significant, a normal t-test will be invoked. Assuming that abnormal returns are normally and independently distributed, abnormal returns are not cross-sectionally correlated. For the null hypothesis dealing with average abnormal returns at a specific time the t-statistic will be denoted by:

$$(13) \quad TS = \sqrt{N} \frac{AAR_t}{\sigma}$$

Because σ is unknown, an estimator needs to be formulated. (14)

$$(14) \quad \hat{\sigma}_t = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (AR_{it} - AAR_t)^2}$$

With this, the t-statistic that checks average abnormal returns will be denoted by: (15)

$$(15) \quad TS = \sqrt{N} \frac{AAR_t}{\hat{\sigma}}$$

Next, to test the statistical significance of cumulative abnormal returns per firm in the event period, a similar t-statistic will be formulated. (16 & 17)

$$(16) \quad \hat{\sigma}_i = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (AR_{it} - CAR_i)^2}$$

$$(17) \quad TS = \sqrt{N} \frac{CAR_i}{\hat{\sigma}}$$

The last t-statistic to be defined is the t-statistic that test the cumulative average abnormal returns. This will test whether firms' returns jointly deviate from zero significantly. (18 & 19)

(18)

$$\hat{\sigma} = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (CAR_i - CAAR)^2}$$

(19)

$$TS = \sqrt{N} \frac{CAAR}{\hat{\sigma}}$$

The estimator for the standard deviation is computed by taking the sample standard deviation of cumulative average abnormal returns. The t-test is then defined by taking the root of the number of observations (firms) in the sample and multiplying it by the cumulative average return divided by the estimator of sample standard deviation.

Chapter 3: Data

Event date definition and dataset

This particular event study starts with the identification of tweets posted by Donald Trump that mention companies in a negative sense.

As mentioned earlier, Trump has tweeted around 35,000 times since joining Twitter in March 2009. To identify which tweets contain information about companies, I referenced Yahoo Finance's Trump Tweet Page. They wrote a special algorithm for the identification of tweets along with Factba.se, which is a research tool that can analyze and identify tweets. This yielded 60 instances for which Donald Trump tweeted about a company in a negative context. Any tweet that was identified as containing a negative context about a company will be defined as an individual event.

To check whether there is stock data available for these 60 companies, I looked at whether the mentioned companies were public or private companies. If the companies were public, their corresponding ticker codes were looked up. Twenty-three companies were excluded from the analysis because they were private companies and thus no stock data was available. The final set of companies *before* matching with the stock data consisted of 37 companies.

The data itself was acquired via the CRSP database. The list of ticker codes containing the 37 companies was used to download the data. For every company, the permno, the full company name, market capitalisation, the daily share price, daily return and the daily value weighted index for market return was downloaded. The value-weighted index was chosen in favor of the equally-weighted index because with the value-weighted index, companies with the highest market capitalization will have the highest relative weight in the index. Given that the Trump tweets are mostly directed at Fortune 500 companies, which generally are companies with a high market capitalization, the value-weighted index is more representative when estimating targeted companies' market model parameters.

After the data was downloaded, it was checked whether the tweet was posted on a trading day (or after the market closed). If it was, the event date was set to be the tweet date, if not, the event date was set to the next trading day. The unedited initial dataset consists of 7 variables containing a little over 89,000 observations.

Preparing the data

To analyze the data, a small dataset was constructed from the tweets with company names, event dates and permno's (if available), which will act as a company identifier. I have added my STATA code to the appendix and will refer to it throughout my description of data handling. For this part, I will refer to (A1.0) of the appendix. For every company with an identifier I generated a variable that counted how many times it was present in the dataset (A1.1) and excluded those companies without one as they are private companies for which no stock data is available. The following step was to merge the dataset containing all the stock data using the company identifier (permno's) (A1.2). If a company's event count was more than 1, meaning that there are more than 1 tweet posted about that company so multiple event periods for an individual company, the daily stock data for that firm was duplicated (A1.3) in order to accommodate for separate evaluation of that stock over the different event windows. The next step was to assign the correct event dates to the correct set of stock observations and assign each group of stock observations belonging to an individual company a number as to identify them. (A1.4)

Application of event study to dataset

Because the dataset contains substantially more stock observations than needed, the dataset needs to be adjusted in order to be able to identify the estimation and event period. (A2.0)

For every company in the dataset, a variable was created that counts the number of observations as trading days (A2.1). Alongside this a 'target' date variable was created that identifies the event date for every firm in the sample and assigns it the observation number (A2.2). After this, the difference between the 'target' and every observation can be calculated (A2.3). So for example, if the event date takes place at the 1700th observation for a particular firm and we are currently looking at the 1650th observation for that company, we are at $t-50$ trading days away from the event.

The next step would be to specify the estimation period and event window. A dummy variable will be created indicating if an observation lies in the estimation period or in the event window (A2.4). In this study, I examine two different event windows with the

same estimation periods. The different event windows, as mentioned earlier, consist of a window that starts at 10 days prior to a tweet and end 10 days after a tweet. The second window is shorter and looks at the immediate short term effects starting one day before, and ending one day after the tweet. The estimation period for both event windows contain 90 days starting at $t-120$ and ending at $t-30$ trading days before the event. Companies for which there was no complete dataset available, because either the tweet took place in 2017 for which no data was available yet, or the COMPUSTAT database did not have share price information available, were excluded. Of the 37 companies I was able to match 33 with complete stock data.

Assessing *Normal* Performance

In order to predict normal performance for every company, I performed regressions for every company separately. (A3.0)

Observations within the estimation windows were used to predict 'normal' performance during the event window(s). The dependent variable here is the observed stock return for a particular company and the independent variable is the value-weighted CRSP index that contains the market return for a given date.

After these regressions were run, the estimated 'normal' return was assigned to observations inside the event window.

With the normal return estimated, I am able to construct a variable that captures the abnormal return inside the event window as the difference between just calculated normal return and the actual observed return (A3.1). A table with the predicted and actual returns is also added to the appendix. The cumulative abnormal return per company was captured in a variable as the sum of the abnormal returns (A3.2). Average abnormal returns were calculated by averaging the abnormal returns at a specific time period t .

The last variable to be constructed before significance testing was the cumulative average abnormal return and it was calculated by averaging the cumulative abnormal returns per company. To check if the last calculation was correct, another one-variable regression was performed for which the coefficient should be the same as the just calculated cumulated average abnormal return, which was the case (A4.1.1).

Testing *Abnormal* Performance

To test abnormal performance, several tests were constructed in Stata. I'd first like to refer to formula's 13, 15, and 17 that are used to calculate t-statistics that test average abnormal returns, cumulative abnormal returns and cumulative average abnormal returns, respectively. These were accordingly translated into stata code which can be referred in appendix A4.1 - A4.3.

Chapter 4: Results

The results will be presented chronologically, starting with the so called citizen period and ending with the presidential period. Per period, the 21-day event window will be discussed first, and after that the 3-day event window results will be discussed to look at the immediate short term effects.

Citizen period

The citizen period spans the entire period prior to Mr. Trump announcing his 2016 presidential bid from the time he has joined twitter in 2009. The sample consists of a subset of 14 companies. The first result that is presented (table 1) are the aggregated abnormal and cumulative abnormal returns for the 21-day event window, accompanied by a t-statistic that tests the significance of the aggregated average abnormal return.

21 Day Event Period

Table 1

Event Day	Average Abnormal Return	T-Statistic	CAAR
-10	-0,176%	-0,43	-0,176%
-9	0,121%	0,52	-0,055%
-8	-0,108%	-0,53	-0,162%
-7	0,068%	0,28	-0,094%
-6	-0,078%	-0,35	-0,172%
-5	0,647%	0,89	0,475%
-4	0,030%	0,11	0,505%
-3	0,826%	2,85***	1,332%
-2	0,029%	0,04	1,361%
-1	-0,017%	-0,08	1,344%
0	-0,089%	-0,06	1,255%
1	-0,225%	-0,91	1,030%
2	-0,135%	-0,49	0,894%
3	0,225%	0,87	1,119%
4	-0,010%	-0,04	1,110%
5	0,116%	0,66	1,226%
6	0,370%	1,60	1,596%
7	0,112%	0,31	1,708%
8	0,014%	0,05	1,722%
9	0,119%	0,60	1,841%
10	-0,336%	-1,50	1,505%

3 Day Event Period

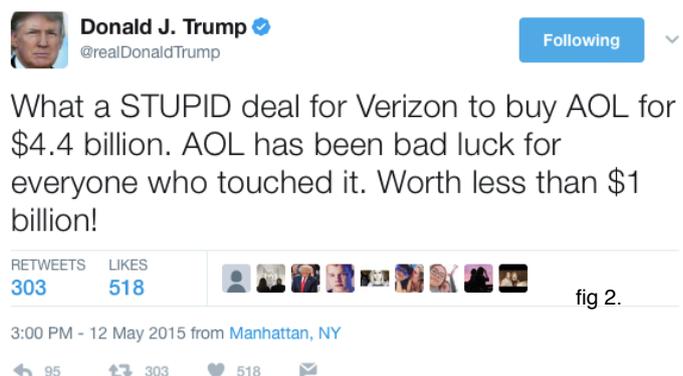
Table 2

Event Day	Average Abnormal Return	T-Statistic	CAAR
-1	0,001%	0,006	0,001%
0	-0,091%	-0,061	-0,089%
1	-0,044%	-0,237	-0,134%

As is visible in table 1, the average abnormal returns of all companies in the subsample is very small and statistically insignificant for the 21 day event window period. This would suggest that in this period, looking at the 21 day event window, Trump tweets do not have a significantly negative effect.

Zooming in on the tweet posting (table 2), when the event window spans 3 days, we see that for the citizen period, there is also little statistical and economic significance for the firms combined.

The individual company significance for both the 21 and 3 day event window is depicted in table 3. Here, some individual statistical significance is visible. Looking the 3 day event window, we see that S&P Global’s cumulative abnormal return is statistically insignificant but economically there is a significant negative drop. S&P Global’s cumulative abnormal return for the 3 day period is -10,46%, which is abnormally large. The question worth asking here is did a Trump tweet cause this or was there an external factor that caused the stock price to drop after which Trump tweeted his outrage about it? The answer seems to be the originating in the former. On August 8 2011, one day before the issue of the tweet, S&P downgraded the credit rating of the United States’ foreign debt for the first time in history, triggering the so called black Monday (Yahoo Finance). Infuriated by this, Donald Trump took to Twitter (fig. 2). The other company that seems to be significantly effected statistically is Coca Cola. On the day this tweet was posted, Coca Cola published its quarterly results that were slightly lower than expected by analysts, causing the decline in value (Reuters). Other cumulative returns that



cumulative returns that are not significant statistically, but rather large economically are the returns from Sony and AOL. For Sony, the decline in its stock price can be attributed largely to the hacking of its computers in December 2014. Considering the AOL case, there is a truly massive positive cumulative abnormal return. On the day of the tweet, the twelfth of May 2015, AOL announced it was merging with Verizon in a \$4.4 billion dollar deal, causing the stock to soar. Trump, again infuriated somehow by this, took to twitter to radiate his anger, with no (negative) effect on the stock price whatsoever.

Individual Company Significance

Table 3

Company Name	21 day event window		3 day event window	
	CAR	T-Statistic	CAR	T-Statistic
Microsoft	2,54%	0,69	1,56%	2,11
Coca Cola	-2,20%	-0,81	-2,81%	-5,34**
Charter Communications	2,40%	0,48	0,04%	0,07
New York Post	4,66%	0,66	0,56%	1,67
Apple	-2,57%	-0,26	-8,52%	-0,99
S&P Global	0,82%	0,06	-10,46%	-2,04*
Procter & Gamle	-4,04%	-0,82	0,39%	0,35
Ford	-4,70%	-1,61	-0,32%	-0,51
JP Morgan	7,27%	1,52	1,61%	1,71
USA Today (Gannet)	-3,10%	-0,59	0,50%	0,46
H&R Block	4,64%	1,37	0,94%	0,53
Sony	-9,38%	-1,14	-3,75%	-1,49
Verizon	0,26%	0,15	-0,22%	-0,39
AOL	26,84%	1,28	18,64%	0,96

Candidate period

The trend established in the citizen period is one in which something happens and Trump reacts to it by venting his opinion on Twitter. The subset of companies Trump tweeted about after he announced his 2016 presidential bid on the fifteenth of June, 2015 are considered next. The total number of companies in this subset is 14.

Again, the 21-day aggregate event period is considered first, and after that, the 3-day aggregate event period is depicted in table 4.

21 Day Event Period

Table 4

Event Day	Average Abnormal Return	T-Statistic	CAAR
-10	-0,170%	-0,76	-0,170%
-9	0,332%	0,97	0,163%
-8	0,041%	0,21	0,204%
-7	-0,009%	-0,03	0,195%
-6	0,196%	0,38	0,390%
-5	-0,163%	-0,67	0,227%
-4	-0,563%	-1,27	-0,336%
-3	0,061%	0,11	-0,275%
-2	-0,015%	-0,03	-0,290%
-1	-0,049%	-0,16	-0,339%
0	-0,213%	-0,64	-0,552%
1	0,211%	0,61	-0,341%
2	-1,042%	-3,074***	-1,383%
3	-0,161%	-0,69	-1,544%
4	0,354%	0,91	-1,190%
5	0,003%	0,01	-1,186%
6	-0,245%	-0,95	-1,431%
7	-0,186%	-0,44	-1,616%
8	-0,207%	-0,38	-1,823%
9	0,356%	0,76	-1,468%
10	0,089%	0,22	-1,379%

Looking at the average abnormal returns of all companies together, we again see nothing substantial. In contrast to the citizen period however, there is a statistically significant negative effect 2 days after the event. There is a significant negative effect on average abnormal returns 2 days after the event, but jointly, no immediate negative effects are visible. The 3 day event window (table 5) shows similar statistically and economically insignificant aggregate results.

3 Day Event Period

Table 5

Event Day	Average Abnormal Return	T-Statistic	CAAR
-1	-0,067%	-0,216	-0,067%
0	-0,213%	-0,644	-0,280%
1	0,017%	0,043	-0,263%

Regarding individual company significance we see some companies that exhibit statistical significance in their cumulative abnormal returns (table 6). For the 21 day period, the cumulative abnormal return for CNN is -5.49% and it is statistically significant at the 5% level, but when evaluated in the 3-day window, we see that the immediate effect of Trump's tweet on its stock return is negligible. The cumulative abnormal stock returns that are statistically significant in the 3 day event window are the stock price from Hewlett-Packard and CNBC. Considering Hewlett-Packard (HP), this is also an example of a tweet by Trump after some externality has taken place. In this case, the tweet came after HP announced it would split up into a separate hardware and software company, causing the stock price to depreciate (Tweakers).

Regarding stocks that have cumulative abnormal returns that are statistically insignificant but have relative large economic significance, we first look at Mylan. Mylan, a company that produces epipens, was caught up in a scandal spiking the prices of those epipens to disproportional levels. The company, being a donor to the Clinton foundation subsequently became a target on Twitter for Mr. Trump (The Daily Caller). Considering Goldman, we see that in the 3 day event window period, the effect of the tweet on cumulative returns is very low. However, with the 21 day period, we see a negative cumulative abnormal return of -6.25%. This return is partially explained by the the overlapping of publishing Goldman's quarterly results and the tweet. The results were 11% lower than previously expected (Goldman).

Individual Company Significance

Table 6

Company Name	21 day event window		3 day event window	
	CAR	T-Statistic	CAR	T-Statistic
Fox News	5,49%	0,71	4,37%	1,36
Wallstreet Journal	4,28%	0,60	-2,42%	-0,73
Twitter	4,91%	0,45	0,94%	0,28
Disney	6,51%	1,42	-0,76%	-0,96
HP	-3,37%	-0,45	-4,26%	-3,56***
New York Times	4,10%	1,66	2,15%	1,89
Mylan	-11,64%	-1,24	0,17%	0,14
CNN	-5,49%	-2,11**	-0,31%	-0,42
Macy's	-0,08%	-0,01	-0,48%	-0,40
Amazon	-3,17%	-0,60	0,45%	0,17
Goldman Sachs	-6,25%	-1,15	-0,55%	-0,28

Individual Company Significance

Table 6

Company Name	21 day event window		3 day event window	
	CAR	T-Statistic	CAR	T-Statistic
CNBC (Comcast Corporation)	-1,70%	-0,45	-2,18%	-3,51**
Google	-9,03%	-1,64	-0,80%	-0,52
T-Mobile	-8,47%	-0,85	-0,16%	-0,03

Presidential period

The next period to be considered is the period after which Donald Trump was elected President of the United States on November 8, 2016. Since the CRSP database is only up to date up until the last day of 2016, this subset of companies consists therefore of only 5 companies.

The aggregate cumulative results are presented in table 7 for the 21 day event period.

21 Day Event Period

Table 7

Event Day	Average Abnormal Return	T-Statistic	CAAR
-10	0,093%	0,16	0,093%
-9	0,426%	0,76	0,520%
-8	0,498%	0,86	1,018%
-7	0,395%	0,75	1,413%
-6	0,765%	1,20	2,178%
-5	-0,486%	-0,63	1,692%
-4	-0,147%	-0,23	1,546%
-3	2,047%	2,34	3,593%
-2	0,819%	0,41	4,412%
-1	-2,114%	-3,46***	2,298%
0	-1,390%	-2,76*	0,908%
1	-0,367%	-1,90	0,541%
2	0,463%	0,82	1,004%
3	1,070%	1,17	2,074%
4	0,750%	0,79	2,824%
5	-0,590%	-1,90*	2,234%
6	-1,079%	-1,46	1,155%
7	-0,633%	-0,62	0,522%
8	0,880%	1,68	1,402%
9	0,454%	2,19**	1,856%
10	-0,204%	-0,26	1,652%

The first thing that is striking is that in this subset, there are statistically significant returns around and on the event date. We see negative abnormal returns 1 day prior to the event and on the event date itself. This could indicate that an external effect was already negatively affecting the aggregated stock returns. Looking at the 3 day event window in table 8, we see negative average abnormal returns on all days and a statistically significant return of -1,75% on the day prior to the event at the 10% level.

Table 8

3 Day Event Period				
Event Day	Average Abnormal Return	T-Statistic	CAAR	
-1	-1,751%	-2,94**	-1,751%	
0	-1,051%	-2,03*	-2,802%	
1	-0,555%	-2,31**	-3,357%	

When we consider the cumulative abnormal returns per individual company (table 9), we see that for the 21 day event window cumulative abnormal returns are not statistically significant at any significance level. In the 3 day event window period however, the cumulative abnormal returns are all negative and three of them statistically significant. This could be an indication that the tweets do have some sort of effect on the stock prices in the negative sense.

Table 9

Company Name	21 day event window		3 day event window	
	CAR	T-Statistic	CAR	T-Statistic
GM (General Motors)	3,59%	0,40	-5,54%	-2,29*
Rexnord	-5,16%	-0,53	-6,50%	-3,07***
Boeing	2,05%	0,58	-1,71%	-2,80**
Lockheed Martin*	n/a	n/a	-1,30%	-0,92
Toyota	6,14%	0,97	-1,74%	-1,70

To investigate further, I have searched for news about the companies on and around the event date i.e. tweet date. In the case of General Motors, there was no news on and around the event date. The tweet by Trump (fig. 3) can be considered a direct threat directed at the company after which the stock price

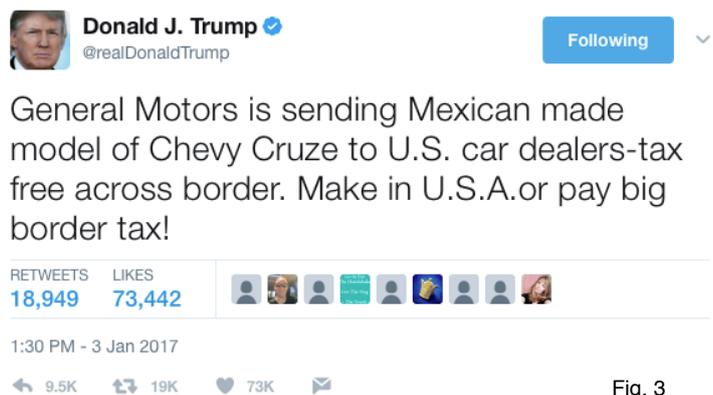


Fig. 3

*Lockheed Martin is excluded from the 21-day period event window because there was insufficient data available to compute all returns in the event window. The 21-day event window flows in to 2017 for which there was no data available in the dataset.

of General motors declined. Considering Rexnord, an industrial company, there was an announcement made by the the firm's management that the firm would be moving to Mexico and continue operations there (Reuters). Hearing the news, Trump again turned to Twitter to declare that this was going to stop. The most famous and well known example of this subset is Boeing. Mr. Trump, when learning that the newly ordered Air Force One project was over budget declared on Twitter that the order should be cancelled immediately, causing Boeing's stock to tumble.

When comparing the 21 day event window with the 3 day event window, it is striking to see that most of the initial negative effects caused by the tweets are reversed in a short amount of time. Only Rexnord still exhibits negative cumulative abnormal returns. The reversal could be caused by the market perceiving the tweets as hollow threats.

Total period

All individual periods have now been assessed and these periods will now be aggregated to see what their joint effect is. We start with the 21 day event window period (table 10). For any given day in the event window, average abnormal returns are relatively low and statistically insignificant. The cumulative average abnormal effect for the entire sample at the end of the 21 day event window is slightly positive at 0.208%.

21 Day Event Period

Table 10

Event Day	Average Abnormal Return	T-Statistic	CAAR
-10	-0,133%	-0,10	-0,133%
-9	0,270%	0,24	0,137%
-8	0,014%	0,02	0,151%
-7	0,072%	0,06	0,223%
-6	0,162%	0,11	0,385%
-5	0,192%	0,09	0,577%
-4	-0,315%	-0,23	0,262%
-3	0,642%	0,36	0,905%
-2	0,112%	0,04	1,017%
-1	-0,312%	-0,25	0,705%
0	-0,307%	-0,07	0,398%
1	-0,076%	-0,07	0,322%
2	-0,409%	-0,32	-0,087%
3	0,256%	0,24	0,169%
4	0,208%	0,15	0,377%
5	-0,017%	-0,01	0,360%
6	-0,045%	-0,04	0,315%
7	-0,035%	-0,02	0,281%
8	-0,061%	-0,04	0,220%
9	0,136%	0,11	0,355%
10	-0,147%	-0,11	0,208%

When the event window is reduced to three days (table 11), we again see very small negative average abnormal returns that are not statistically significant at any level. This would imply that for both event windows, the effect of the tweets on the aggregated sample of is non-existent or negligible.

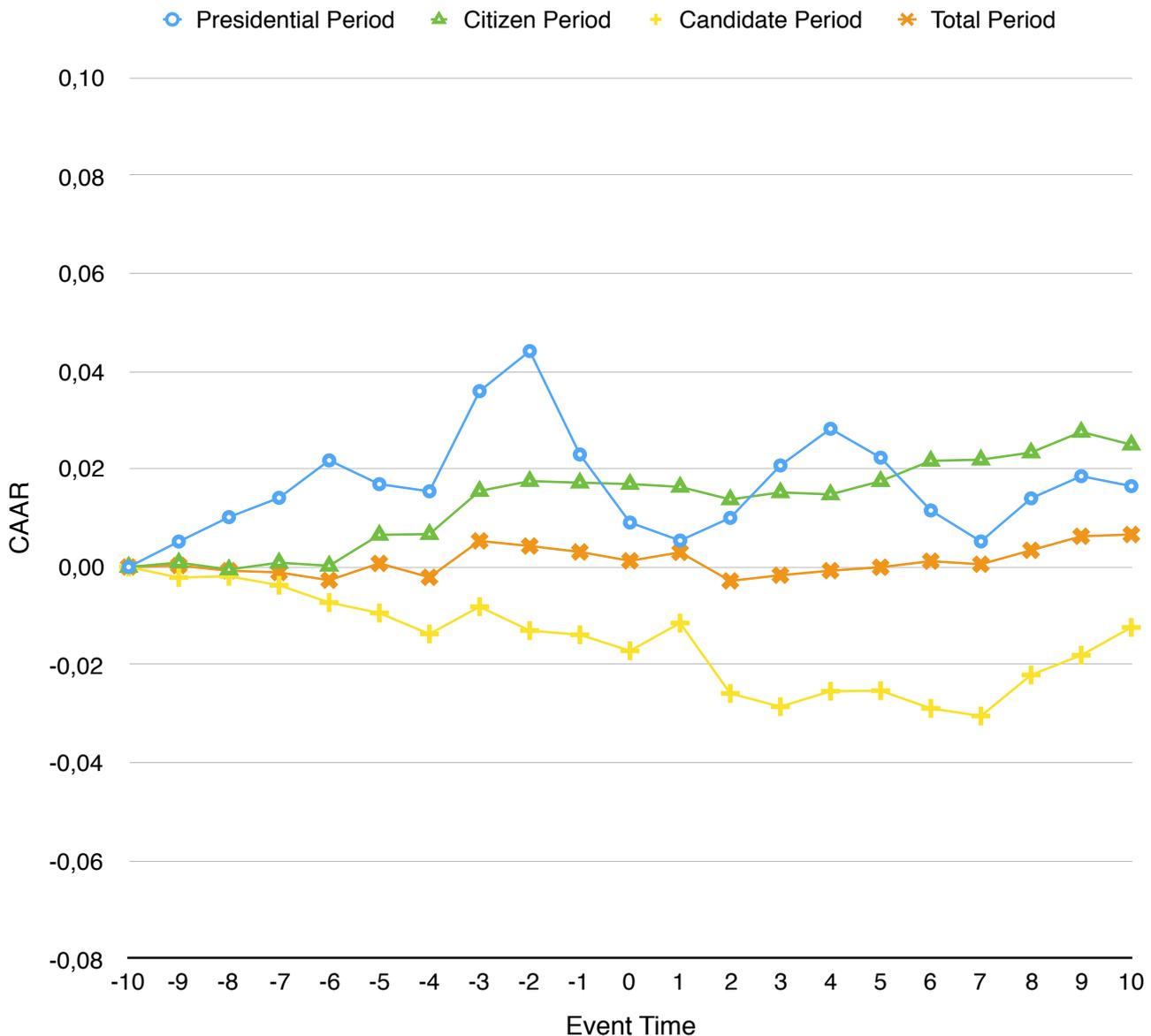
3 Day Event Period

Table 11

Event Day	Average Abnormal Return	T-Statistic	CAAR
-1	-0,311%	-1,44	-0,311%
0	-0,288%	-0,40	-0,599%
1	-0,115%	-0,58	-0,714%

To make this more illustrative, I've created a graph (fig. 4) that illustrates the movement of the cumulative average abnormal returns per period over the 21 day event window. On the Y-axis cumulative abnormal returns are positioned and the X-axis depicts event time, starting at t-10. Looking at the graph, we see that the most volatile period is the presidential period but since this subset consists of only a few companies that is not surprising. Over time we see no substantial negative cumulative abnormal returns, whatever the period.

fig. 4



Chapter 5: Concluding Remarks

Looking back at the results, the analyses indicate that for the citizen period in both event windows, there is not enough evidence to reject the null hypothesis of negative average abnormal returns caused by the tweeting behavior of Donald Trump. Regarding individual company significance, of the 14 companies observed in the sample, the null hypothesis of significant negative cumulative abnormal is only rejected once (at the 5% level) in the case of Coca Cola, which can be attributed to missing revenue expectations (Reuters). Overall, we see in this period a cumulative average abnormal return of -0,089% on the event day that is statistically and economically insignificant. The total cumulative average abnormal return over the 21-day event window is positive at 1,505%, indicating that for this period there is no evidence whatsoever that Trump's tweets have a negative effect on stock valuation in the short and long term. There is some economical significance visible as has been explained in chapter 4.

For the candidate period we again observe that for the 3-day event window, there is no statistical significance to be noticed on an around the event day. The average abnormal return in this period on the event day was -0,280%. Not enough to reject the null hypothesis of cumulative average abnormal returns that are statistically different from zero, both for the 3-day event window, and for the 21-day event window. Looking at individual company significance for this period, we see that the null hypothesis of no cumulative abnormal returns can be rejected 1 out of 14 times (at a 5% significance level) for the 3-day event window. As discussed in chapter 4, the decline can be attributed to an external event. For the 21-day event window, we see that there is a statistically significant negative cumulative abnormal return for CNN (-5,49%), but since the cumulative abnormal return of CNN for the 3-day period is almost negligible (-0,31%) and statistically insignificant at any significance level, we can assume that the tweet posted was not the cause of the stock price depreciation.

The last period, the presidential period, has different results. We observe that the average abnormal returns over the companies in this period are negative (-1,05%) but statistically insignificant at any level on the event day itself. In this instance, there is not enough evidence that supports the rejection of the null hypothesis that the average abnormal returns are different from zero in the 3-day event window (table 6). Although returns are negative, the economical average significance of -1,05% is rather low. When we look at the 21-day event window, we observe similar results around the event date (table 7)

that are statistically significant. The individual results indicate that in this case, in most cases there is a negative, but statistically insignificant effect of a tweet. Further research suggested that this short-term depreciation is accompanied by a direct threat against the company by the President on Twitter. When again looking at the aggregated 21-day event window we see that the stock prices have all recovered with a cumulative average abnormal return of 1,65% indicating that the negative effect of the tweet and threat are already reversed within a few days.

When comparing the three periods we see that in the first two periods, there is little effect of tweets on stock prices. Tweets are posted after some external event has become public knowledge which has already caused the stock to fluctuate. Regarding the presidential period, we see a reversal of this trend. Tweets are now directed as threats against the company and in the absence of external news, this could contribute to the stock price depreciation in the short term. However, this initial negative effect is mitigated in the days following up to the event, suggesting that the effect of Trump Tweets on firm valuation are short-lived.

Further research could be conducted by appending the results of this study with new tweets posted about companies by President Trump in the future, for however long that may be. The Trump Presidency is only in its fourth month out of the total of 48 at a minimum. A lot can happen in the remainder of the Administration's term.

Appendix: Beta's per company

Beta per Company

Company Name	β
Microsoft	.759933
Coca Cola	.6933138
Charter Communications	.901603
GM (General Motors)	1.260192
Rexnord	1.846493
Fox News	1.329641
New York Post	.8061559
Twitter	1.370373
Apple	.3981448
S&P Global	1.036028
Procter & Gamle	.4442975
Boeing	1.221091
Ford	1.257598
Disney	.9825638
HP	1.06296
New York Times	.9641707
JP Morgan	1.206282
Lockheed Martin	.602149
USA Today	1.337778
H&R Block	1.087006
Sony	.5735037
Verizon	.5962342
Mylan	1.576502
CNN	.9748825
Wall Street Journal	1.882391
Macy's	.8011875
Amazon	1.272291
Goldman Sachs	1.154776
CNBC (Comcast Corporation)	.9733778
Google	.9016996
T-Mobile	.8481145
Toyota	.7014415
AOL	1.437563

Appendix: Predicted Returns vs. Actual Returns

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Microsoft	18/09/2013	1,18%	1,03%	-0,15%
Microsoft	19/09/2013	0,96%	-0,02%	-0,98%
Microsoft	20/09/2013	-2,52%	-0,48%	2,04%
Microsoft	23/09/2013	-0,16%	-0,24%	-0,09%
Microsoft	24/09/2013	-0,87%	-0,02%	0,85%
Microsoft	25/09/2013	0,15%	-0,05%	-0,21%
Microsoft	26/09/2013	0,82%	0,36%	-0,45%
Microsoft	27/09/2013	1,53%	-0,20%	-1,73%
Microsoft	30/09/2013	0,03%	-0,29%	-0,32%
Microsoft	01/10/2013	0,90%	0,73%	-0,17%
Microsoft	02/10/2013	1,01%	0,02%	-1,00%
Microsoft	03/10/2013	-0,18%	-0,58%	-0,40%
Microsoft	04/10/2013	0,06%	0,59%	0,53%
Microsoft	07/10/2013	-1,71%	-0,57%	1,15%
Microsoft	08/10/2013	-0,87%	-0,93%	-0,06%
Microsoft	09/10/2013	0,18%	0,04%	-0,14%
Microsoft	10/10/2013	2,09%	1,66%	-0,42%
Microsoft	11/10/2013	1,10%	0,60%	-0,49%
Microsoft	14/10/2013	0,94%	0,39%	-0,55%
Microsoft	15/10/2013	0,12%	-0,44%	-0,56%
Microsoft	16/10/2013	0,43%	1,04%	0,61%
Coca Cola	02/10/2012	-0,10%	0,08%	0,18%
Coca Cola	03/10/2012	-0,26%	0,16%	0,42%
Coca Cola	04/10/2012	0,24%	0,53%	0,29%
Coca Cola	05/10/2012	0,65%	-0,03%	-0,68%
Coca Cola	08/10/2012	0,00%	-0,25%	-0,25%
Coca Cola	09/10/2012	-0,05%	-0,68%	-0,63%
Coca Cola	10/10/2012	-1,22%	-0,39%	0,83%
Coca Cola	11/10/2012	0,05%	0,11%	0,05%
Coca Cola	12/10/2012	0,31%	-0,25%	-0,56%
Coca Cola	15/10/2012	-0,26%	0,50%	0,76%
Coca Cola	16/10/2012	-0,60%	0,68%	1,29%
Coca Cola	17/10/2012	-0,42%	0,34%	0,76%
Coca Cola	18/10/2012	0,26%	-0,20%	-0,46%
Coca Cola	19/10/2012	-1,16%	-1,09%	0,07%
Coca Cola	22/10/2012	-0,45%	0,01%	0,46%
Coca Cola	23/10/2012	-1,67%	-0,90%	0,76%
Coca Cola	24/10/2012	0,74%	-0,19%	-0,92%
Coca Cola	25/10/2012	0,57%	0,22%	-0,35%
Coca Cola	26/10/2012	-0,13%	-0,10%	0,04%
Coca Cola	31/10/2012	0,38%	0,15%	-0,23%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Coca Cola	01/11/2012	0,40%	0,76%	0,36%
Charter Communications	06/02/2012	0,24%	0,06%	-0,18%
Charter Communications	07/02/2012	-0,81%	0,27%	1,08%
Charter Communications	08/02/2012	0,48%	0,33%	-0,16%
Charter Communications	09/02/2012	1,15%	0,24%	-0,91%
Charter Communications	10/02/2012	-0,34%	-0,61%	-0,27%
Charter Communications	13/02/2012	2,36%	0,80%	-1,55%
Charter Communications	14/02/2012	0,08%	-0,00%	-0,09%
Charter Communications	15/02/2012	3,67%	-0,25%	-3,92%
Charter Communications	16/02/2012	0,47%	1,26%	0,80%
Charter Communications	17/02/2012	0,54%	0,27%	-0,28%
Charter Communications	21/02/2012	-0,24%	0,16%	0,40%
Charter Communications	22/02/2012	0,03%	-0,14%	-0,17%
Charter Communications	23/02/2012	1,24%	0,65%	-0,59%
Charter Communications	24/02/2012	-0,11%	0,28%	0,39%
Charter Communications	27/02/2012	0,22%	0,22%	-0,00%
Charter Communications	28/02/2012	-0,02%	0,40%	0,42%
Charter Communications	29/02/2012	-0,24%	-0,37%	-0,14%
Charter Communications	01/03/2012	-0,27%	0,75%	1,02%
Charter Communications	02/03/2012	-1,08%	-0,30%	0,78%
Charter Communications	05/03/2012	-0,34%	-0,27%	0,07%
Charter Communications	06/03/2012	-2,33%	-1,42%	0,91%
GM (General Motors)	18/11/2016	-1,26%	-0,12%	1,13%
GM (General Motors)	21/11/2016	0,03%	1,04%	1,01%
GM (General Motors)	22/11/2016	2,42%	0,44%	-1,98%
GM (General Motors)	23/11/2016	0,15%	0,18%	0,03%
GM (General Motors)	25/11/2016	1,15%	0,52%	-0,63%
GM (General Motors)	28/11/2016	-0,58%	-0,70%	-0,12%
GM (General Motors)	29/11/2016	1,53%	0,16%	-1,37%
GM (General Motors)	30/11/2016	-0,12%	-0,16%	-0,04%
GM (General Motors)	01/12/2016	5,50%	-0,48%	-5,98%
GM (General Motors)	02/12/2016	-2,80%	0,15%	2,95%
GM (General Motors)	05/12/2016	-1,33%	0,97%	2,30%
GM (General Motors)	06/12/2016	0,37%	0,66%	0,28%
GM (General Motors)	07/12/2016	3,51%	1,60%	-1,91%
GM (General Motors)	08/12/2016	0,33%	0,52%	0,19%
GM (General Motors)	09/12/2016	3,40%	0,55%	-2,85%
GM (General Motors)	12/12/2016	-1,49%	-0,25%	1,24%
GM (General Motors)	13/12/2016	0,70%	0,77%	0,07%
GM (General Motors)	14/12/2016	-3,77%	-1,16%	2,61%
GM (General Motors)	15/12/2016	0,81%	0,51%	-0,30%
GM (General Motors)	16/12/2016	0,36%	-0,10%	-0,46%
GM (General Motors)	19/12/2016	0,08%	0,32%	0,24%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Rexnord	18/11/2016	0,00%	-0,47%	-0,47%
Rexnord	21/11/2016	2,54%	1,23%	-1,31%
Rexnord	22/11/2016	1,07%	0,35%	-0,72%
Rexnord	23/11/2016	1,94%	-0,03%	-1,98%
Rexnord	25/11/2016	-0,14%	0,47%	0,61%
Rexnord	28/11/2016	-2,04%	-1,32%	0,72%
Rexnord	29/11/2016	-1,72%	-0,06%	1,66%
Rexnord	30/11/2016	3,77%	-0,52%	-4,30%
Rexnord	01/12/2016	-4,59%	-0,99%	3,60%
Rexnord	02/12/2016	-3,43%	-0,07%	3,36%
Rexnord	05/12/2016	-1,09%	1,13%	2,22%
Rexnord	06/12/2016	-0,25%	0,67%	0,92%
Rexnord	07/12/2016	1,20%	2,05%	0,85%
Rexnord	08/12/2016	4,25%	0,47%	-3,78%
Rexnord	09/12/2016	-1,23%	0,52%	1,75%
Rexnord	12/12/2016	-0,77%	-0,66%	0,11%
Rexnord	13/12/2016	-2,42%	0,83%	3,25%
Rexnord	14/12/2016	-3,27%	-1,99%	1,28%
Rexnord	15/12/2016	0,61%	0,45%	-0,16%
Rexnord	16/12/2016	0,20%	-0,44%	-0,64%
Rexnord	19/12/2016	1,98%	0,18%	-1,81%
Fox News	25/02/2016	0,74%	1,55%	0,80%
Fox News	26/02/2016	0,46%	0,13%	-0,33%
Fox News	29/02/2016	-0,92%	-0,69%	0,22%
Fox News	01/03/2016	-0,46%	3,06%	3,52%
Fox News	02/03/2016	1,11%	0,84%	-0,27%
Fox News	03/03/2016	0,18%	0,84%	0,65%
Fox News	04/03/2016	0,82%	0,64%	-0,18%
Fox News	07/03/2016	2,82%	0,53%	-2,29%
Fox News	08/03/2016	-3,45%	-1,72%	1,73%
Fox News	09/03/2016	1,56%	0,82%	-0,73%
Fox News	10/03/2016	0,00%	-0,07%	-0,07%
Fox News	11/03/2016	5,95%	2,39%	-3,56%
Fox News	14/03/2016	-1,62%	-0,11%	1,50%
Fox News	15/03/2016	0,09%	-0,50%	-0,58%
Fox News	16/03/2016	4,24%	1,09%	-3,15%
Fox News	17/03/2016	3,15%	1,20%	-1,95%
Fox News	18/03/2016	-1,05%	0,61%	1,65%
Fox News	21/03/2016	0,57%	0,16%	-0,40%
Fox News	22/03/2016	2,10%	0,04%	-2,06%
Fox News	23/03/2016	-0,79%	-1,16%	-0,37%
Fox News	24/03/2016	-0,32%	0,08%	0,40%
New York Post	21/01/2015	0,07%	0,29%	0,22%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
New York Post	22/01/2015	1,73%	1,11%	-0,62%
New York Post	23/01/2015	-0,27%	-0,41%	-0,14%
New York Post	26/01/2015	2,18%	0,28%	-1,90%
New York Post	27/01/2015	-0,47%	-0,88%	-0,41%
New York Post	28/01/2015	-1,07%	-1,22%	-0,15%
New York Post	29/01/2015	-1,97%	0,60%	2,57%
New York Post	30/01/2015	-0,14%	-1,05%	-0,92%
New York Post	02/02/2015	0,28%	0,91%	0,63%
New York Post	03/02/2015	4,49%	1,14%	-3,35%
New York Post	04/02/2015	-0,13%	-0,45%	-0,32%
Wall Street Journal	22/01/2015	1,73%	1,08%	-0,65%
Wall Street Journal	23/01/2015	-0,27%	-0,43%	-0,16%
Wall Street Journal	26/01/2015	2,18%	0,26%	-1,93%
Wall Street Journal	27/01/2015	-0,47%	-0,90%	-0,43%
Wall Street Journal	28/01/2015	-1,07%	-1,24%	-0,17%
Wall Street Journal	29/01/2015	-1,97%	0,57%	2,54%
Wall Street Journal	30/01/2015	-0,14%	-1,08%	-0,94%
Wall Street Journal	02/02/2015	0,28%	0,88%	0,60%
Wall Street Journal	03/02/2015	4,49%	1,10%	-3,38%
Wall Street Journal	04/02/2015	-0,13%	-0,47%	-0,34%
Twitter	17/10/2016	-0,89%	-0,06%	0,83%
Twitter	18/10/2016	0,60%	1,19%	0,59%
Twitter	19/10/2016	1,43%	0,69%	-0,74%
Twitter	20/10/2016	-1,00%	0,05%	1,05%
Twitter	21/10/2016	7,04%	0,27%	-6,77%
Twitter	24/10/2016	-0,33%	0,89%	1,22%
Twitter	25/10/2016	-4,27%	-0,31%	3,96%
Twitter	26/10/2016	0,17%	-0,10%	-0,28%
Twitter	27/10/2016	0,64%	-0,27%	-0,91%
Twitter	28/10/2016	1,49%	-0,07%	-1,56%
Twitter	31/10/2016	1,64%	0,35%	-1,30%
Twitter	01/11/2016	-2,56%	-0,64%	1,92%
Twitter	02/11/2016	0,69%	-0,78%	-1,47%
Twitter	03/11/2016	-0,17%	-0,29%	-0,12%
Twitter	04/11/2016	2,50%	0,11%	-2,39%
Twitter	07/11/2016	2,16%	3,15%	0,99%
Twitter	08/11/2016	-0,16%	0,77%	0,94%
Twitter	09/11/2016	4,08%	1,93%	-2,15%
Twitter	10/11/2016	-3,97%	0,54%	4,51%
Twitter	11/11/2016	0,98%	0,32%	-0,66%
Twitter	14/11/2016	3,18%	0,60%	-2,58%
Apple	13/01/2014	0,52%	-0,27%	-0,80%
Apple	14/01/2014	1,99%	0,60%	-1,39%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Twitter	19/10/2016	1,43%	0,69%	-0,74%
Twitter	20/10/2016	-1,00%	0,05%	1,05%
Twitter	21/10/2016	7,04%	0,27%	-6,77%
Twitter	24/10/2016	-0,33%	0,89%	1,22%
Twitter	25/10/2016	-4,27%	-0,31%	3,96%
Twitter	26/10/2016	0,17%	-0,10%	-0,28%
Twitter	27/10/2016	0,64%	-0,27%	-0,91%
Twitter	28/10/2016	1,49%	-0,07%	-1,56%
Twitter	31/10/2016	1,64%	0,35%	-1,30%
Twitter	01/11/2016	-2,56%	-0,64%	1,92%
Twitter	02/11/2016	0,69%	-0,78%	-1,47%
Twitter	03/11/2016	-0,17%	-0,29%	-0,12%
Twitter	04/11/2016	2,50%	0,11%	-2,39%
Twitter	07/11/2016	2,16%	3,15%	0,99%
Twitter	08/11/2016	-0,16%	0,77%	0,94%
Twitter	09/11/2016	4,08%	1,93%	-2,15%
Twitter	10/11/2016	-3,97%	0,54%	4,51%
Twitter	11/11/2016	0,98%	0,32%	-0,66%
Twitter	14/11/2016	3,18%	0,60%	-2,58%
Apple	13/01/2014	0,52%	-0,27%	-0,80%
Apple	14/01/2014	1,99%	0,60%	-1,39%
Apple	15/01/2014	2,01%	0,39%	-1,61%
Apple	16/01/2014	-0,56%	0,18%	0,74%
Apple	17/01/2014	-2,45%	0,05%	2,50%
Apple	21/01/2014	1,55%	0,33%	-1,23%
Apple	22/01/2014	0,44%	0,25%	-0,20%
Apple	23/01/2014	0,85%	-0,13%	-0,98%
Apple	24/01/2014	-1,82%	-0,65%	1,17%
Apple	27/01/2014	0,81%	-0,07%	-0,88%
Apple	28/01/2014	-7,99%	0,48%	8,48%
Apple	29/01/2014	-1,14%	-0,21%	0,93%
Apple	30/01/2014	-0,19%	0,65%	0,84%
Apple	31/01/2014	0,16%	-0,04%	-0,20%
Apple	03/02/2014	0,19%	-0,73%	-0,92%
Apple	04/02/2014	1,45%	0,49%	-0,95%
Apple	05/02/2014	0,75%	0,10%	-0,64%
Apple	06/02/2014	-0,02%	0,65%	0,67%
Apple	07/02/2014	1,40%	0,69%	-0,70%
Apple	10/02/2014	1,79%	0,25%	-1,54%
Apple	11/02/2014	1,32%	0,61%	-0,70%
S&P Global	26/07/2011	0,14%	-0,36%	-0,50%
S&P Global	27/07/2011	-2,02%	-2,14%	-0,12%
S&P Global	28/07/2011	-0,98%	-0,21%	0,77%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
S&P Global	29/07/2011	-2,46%	-0,48%	1,98%
S&P Global	01/08/2011	-0,46%	-0,27%	0,19%
S&P Global	02/08/2011	7,29%	-2,55%	-9,84%
S&P Global	03/08/2011	0,50%	0,59%	0,09%
S&P Global	04/08/2011	-3,25%	-5,11%	-1,87%
S&P Global	05/08/2011	-3,43%	-0,39%	3,04%
S&P Global	08/08/2011	-8,63%	-7,02%	1,61%
S&P Global	09/08/2011	-1,47%	5,41%	6,88%
S&P Global	10/08/2011	-5,88%	-3,92%	1,96%
S&P Global	11/08/2011	4,44%	4,77%	0,33%
S&P Global	12/08/2011	2,30%	0,60%	-1,70%
S&P Global	15/08/2011	3,26%	2,46%	-0,79%
S&P Global	16/08/2011	-0,49%	-1,04%	-0,55%
S&P Global	17/08/2011	3,20%	0,17%	-3,02%
S&P Global	18/08/2011	-7,24%	-4,59%	2,65%
S&P Global	19/08/2011	-0,40%	-1,49%	-1,08%
S&P Global	22/08/2011	0,11%	0,11%	-0,00%
S&P Global	23/08/2011	4,45%	3,60%	-0,85%
Procter & Gamle	27/04/2012	-3,63%	0,18%	3,81%
Procter & Gamle	30/04/2012	-1,24%	-0,18%	1,06%
Procter & Gamle	01/05/2012	-0,11%	0,22%	0,33%
Procter & Gamle	02/05/2012	0,64%	-0,09%	-0,73%
Procter & Gamle	03/05/2012	0,83%	-0,44%	-1,27%
Procter & Gamle	04/05/2012	-0,36%	-0,69%	-0,33%
Procter & Gamle	07/05/2012	-0,05%	0,03%	0,08%
Procter & Gamle	08/05/2012	-0,14%	-0,23%	-0,09%
Procter & Gamle	09/05/2012	-0,76%	-0,27%	0,49%
Procter & Gamle	10/05/2012	0,74%	0,13%	-0,61%
Procter & Gamle	11/05/2012	-0,72%	-0,12%	0,60%
Procter & Gamle	14/05/2012	-0,16%	-0,53%	-0,38%
Procter & Gamle	15/05/2012	0,22%	-0,26%	-0,48%
Procter & Gamle	16/05/2012	0,89%	-0,22%	-1,11%
Procter & Gamle	17/05/2012	-0,51%	-0,70%	-0,19%
Procter & Gamle	18/05/2012	-0,69%	-0,35%	0,34%
Procter & Gamle	21/05/2012	-0,20%	0,80%	1,00%
Procter & Gamle	22/05/2012	-0,38%	-0,01%	0,36%
Procter & Gamle	23/05/2012	-1,20%	0,13%	1,33%
Procter & Gamle	24/05/2012	0,29%	0,05%	-0,24%
Procter & Gamle	25/05/2012	-0,13%	-0,06%	0,07%
Boeing	21/11/2016	0,46%	0,95%	0,49%
Boeing	22/11/2016	1,70%	0,37%	-1,34%
Boeing	23/11/2016	0,15%	0,11%	-0,04%
Boeing	25/11/2016	0,20%	0,44%	0,24%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Boeing	25/11/2016	0,20%	0,44%	0,24%
Boeing	28/11/2016	-0,18%	-0,74%	-0,56%
Boeing	29/11/2016	1,25%	0,09%	-1,15%
Boeing	30/11/2016	-0,71%	-0,21%	0,50%
Boeing	01/12/2016	1,22%	-0,52%	-1,74%
Boeing	02/12/2016	-0,09%	0,09%	0,18%
Boeing	05/12/2016	-0,06%	0,88%	0,94%
Boeing	06/12/2016	0,05%	0,58%	0,52%
Boeing	07/12/2016	1,25%	1,49%	0,24%
Boeing	08/12/2016	0,81%	0,44%	-0,37%
Boeing	09/12/2016	0,71%	0,48%	-0,23%
Boeing	12/12/2016	0,43%	-0,30%	-0,73%
Boeing	13/12/2016	-0,32%	0,68%	1,00%
Boeing	14/12/2016	-1,40%	-1,18%	0,21%
Boeing	15/12/2016	-0,45%	0,43%	0,88%
Boeing	16/12/2016	0,47%	-0,16%	-0,63%
Boeing	19/12/2016	1,09%	0,25%	-0,84%
Boeing	20/12/2016	0,13%	0,51%	0,37%
Ford	06/04/2015	-0,19%	0,86%	1,05%
Ford	07/04/2015	-0,63%	-0,23%	0,39%
Ford	08/04/2015	0,50%	0,46%	-0,04%
Ford	09/04/2015	-0,19%	0,46%	0,65%
Ford	10/04/2015	0,50%	0,62%	0,12%
Ford	13/04/2015	-1,00%	-0,44%	0,56%
Ford	14/04/2015	0,63%	0,27%	-0,36%
Ford	15/04/2015	0,63%	0,81%	0,19%
Ford	16/04/2015	-0,81%	-0,02%	0,79%
Ford	17/04/2015	-1,13%	-1,38%	-0,25%
Ford	20/04/2015	0,95%	1,05%	0,10%
Ford	21/04/2015	-0,57%	-0,09%	0,47%
Ford	22/04/2015	0,57%	0,55%	-0,02%
Ford	23/04/2015	-0,94%	0,47%	1,42%
Ford	24/04/2015	0,06%	0,18%	0,12%
Ford	27/04/2015	0,82%	-0,56%	-1,39%
Ford	28/04/2015	1,01%	0,33%	-0,67%
Ford	29/04/2015	-0,25%	-0,47%	-0,22%
Ford	30/04/2015	-1,37%	-1,32%	0,06%
Ford	01/05/2015	0,06%	1,20%	1,14%
Ford	04/05/2015	-0,19%	0,41%	0,60%
Disney	19/10/2015	1,14%	-0,04%	-1,18%
Disney	20/10/2015	0,34%	-0,09%	-0,43%
Disney	21/10/2015	0,23%	-0,77%	-1,00%
Disney	22/10/2015	2,87%	1,39%	-1,48%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Disney	23/10/2015	-0,14%	0,96%	1,10%
Disney	26/10/2015	0,38%	-0,25%	-0,63%
Disney	27/10/2015	0,22%	-0,41%	-0,63%
Disney	28/10/2015	0,50%	1,35%	0,85%
Disney	29/10/2015	0,61%	-0,21%	-0,82%
Disney	30/10/2015	-1,13%	-0,37%	0,76%
Disney	02/11/2015	1,14%	1,25%	0,10%
Disney	03/11/2015	0,43%	0,33%	-0,11%
Disney	04/11/2015	-1,98%	-0,33%	1,65%
Disney	05/11/2015	-0,22%	-0,13%	0,09%
Disney	06/11/2015	2,36%	-0,02%	-2,38%
Disney	09/11/2015	0,65%	-0,93%	-1,58%
Disney	10/11/2015	0,86%	0,13%	-0,73%
Disney	11/11/2015	-0,77%	-0,38%	0,39%
Disney	12/11/2015	-0,27%	-1,42%	-1,15%
Disney	13/11/2015	-1,18%	-0,94%	0,24%
Disney	16/11/2015	0,94%	1,36%	0,42%
HP	04/09/2015	-4,05%	-1,50%	2,55%
HP	08/09/2015	2,22%	2,48%	0,25%
HP	09/09/2015	-1,20%	-1,40%	-0,20%
HP	10/09/2015	0,26%	0,43%	0,17%
HP	11/09/2015	-0,66%	0,30%	0,96%
HP	14/09/2015	-0,41%	-0,49%	-0,08%
HP	15/09/2015	0,26%	1,18%	0,92%
HP	16/09/2015	5,02%	0,98%	-4,04%
HP	17/09/2015	-3,16%	-0,12%	3,04%
HP	18/09/2015	-3,74%	-1,67%	2,06%
HP	21/09/2015	-0,38%	0,31%	0,69%
HP	22/09/2015	-2,99%	-1,48%	1,51%
HP	23/09/2015	-0,62%	-0,41%	0,21%
HP	24/09/2015	-0,90%	-0,43%	0,48%
HP	25/09/2015	-0,99%	-0,27%	0,72%
HP	28/09/2015	-1,76%	-2,94%	-1,18%
HP	29/09/2015	0,33%	-0,13%	-0,46%
HP	30/09/2015	3,89%	2,03%	-1,86%
HP	01/10/2015	-1,02%	0,17%	1,18%
HP	02/10/2015	2,84%	1,57%	-1,27%
HP	05/10/2015	4,26%	1,96%	-2,30%
New York Times	05/08/2016	0,78%	0,64%	-0,14%
New York Times	08/08/2016	-0,55%	-0,13%	0,41%
New York Times	09/08/2016	0,16%	-0,03%	-0,19%
New York Times	10/08/2016	-0,70%	-0,41%	0,30%
New York Times	11/08/2016	-0,16%	0,31%	0,47%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
New York Times	12/08/2016	0,79%	-0,19%	-0,98%
New York Times	15/08/2016	1,33%	0,24%	-1,09%
New York Times	16/08/2016	-0,39%	-0,67%	-0,29%
New York Times	17/08/2016	0,16%	-0,05%	-0,21%
New York Times	18/08/2016	0,15%	0,19%	0,03%
New York Times	19/08/2016	0,85%	-0,32%	-1,17%
New York Times	22/08/2016	0,84%	-0,18%	-1,02%
New York Times	23/08/2016	0,08%	0,14%	0,06%
New York Times	24/08/2016	-0,76%	-0,72%	0,04%
New York Times	25/08/2016	0,08%	-0,20%	-0,27%
New York Times	26/08/2016	-0,31%	-0,31%	-0,01%
New York Times	29/08/2016	-0,46%	0,36%	0,82%
New York Times	30/08/2016	0,31%	-0,29%	-0,60%
New York Times	31/08/2016	-0,61%	-0,40%	0,22%
New York Times	01/09/2016	-0,08%	-0,07%	0,01%
New York Times	02/09/2016	0,93%	0,43%	-0,50%
JP Morgan	08/11/2013	4,47%	1,40%	-3,08%
JP Morgan	11/11/2013	0,26%	0,03%	-0,23%
JP Morgan	12/11/2013	-0,24%	-0,37%	-0,13%
JP Morgan	13/11/2013	0,31%	0,91%	0,60%
JP Morgan	14/11/2013	0,48%	0,45%	-0,03%
JP Morgan	15/11/2013	0,86%	0,44%	-0,42%
JP Morgan	18/11/2013	1,59%	-0,65%	-2,24%
JP Morgan	19/11/2013	0,74%	-0,51%	-1,25%
JP Morgan	20/11/2013	-0,09%	-0,49%	-0,40%
JP Morgan	21/11/2013	2,00%	0,95%	-1,05%
JP Morgan	22/11/2013	0,42%	0,45%	0,03%
JP Morgan	25/11/2013	0,33%	-0,26%	-0,59%
JP Morgan	26/11/2013	-0,83%	0,03%	0,86%
JP Morgan	27/11/2013	0,54%	0,22%	-0,32%
JP Morgan	29/11/2013	-0,45%	-0,07%	0,38%
JP Morgan	02/12/2013	-0,42%	-0,53%	-0,12%
JP Morgan	03/12/2013	-0,21%	-0,54%	-0,33%
JP Morgan	04/12/2013	0,58%	-0,23%	-0,81%
JP Morgan	05/12/2013	-2,40%	-0,51%	1,88%
JP Morgan	06/12/2013	0,43%	1,07%	0,64%
JP Morgan	09/12/2013	0,80%	0,13%	-0,67%
USA Today (Gannet)	21/05/2012	-0,69%	2,29%	2,98%
USA Today (Gannet)	22/05/2012	0,00%	-0,15%	-0,15%
USA Today (Gannet)	23/05/2012	-0,39%	0,29%	0,67%
USA Today (Gannet)	24/05/2012	2,18%	0,04%	-2,15%
USA Today (Gannet)	25/05/2012	-0,92%	-0,29%	0,63%
USA Today (Gannet)	29/05/2012	1,39%	1,40%	0,02%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
USA Today (Gannet)	30/05/2012	-1,82%	-2,18%	-0,36%
USA Today (Gannet)	31/05/2012	1,08%	-0,36%	-1,44%
USA Today (Gannet)	01/06/2012	-5,59%	-3,38%	2,21%
USA Today (Gannet)	04/06/2012	0,41%	-0,22%	-0,62%
USA Today (Gannet)	05/06/2012	1,37%	0,96%	-0,41%
USA Today (Gannet)	06/06/2012	2,39%	2,93%	0,54%
USA Today (Gannet)	07/06/2012	-1,17%	-0,27%	0,89%
USA Today (Gannet)	08/06/2012	0,16%	0,87%	0,71%
USA Today (Gannet)	11/06/2012	-0,94%	-1,95%	-1,01%
USA Today (Gannet)	12/06/2012	1,51%	1,48%	-0,03%
USA Today (Gannet)	13/06/2012	-1,56%	-1,06%	0,50%
USA Today (Gannet)	14/06/2012	2,07%	1,19%	-0,88%
USA Today (Gannet)	15/06/2012	0,93%	1,26%	0,33%
USA Today (Gannet)	18/06/2012	-0,54%	0,21%	0,75%
USA Today (Gannet)	19/06/2012	1,55%	1,46%	-0,09%
H&R Block	05/01/2015	-1,81%	-1,95%	-0,13%
H&R Block	06/01/2015	-0,62%	-1,00%	-0,39%
H&R Block	07/01/2015	0,87%	1,23%	0,36%
H&R Block	08/01/2015	1,75%	1,87%	0,12%
H&R Block	09/01/2015	0,57%	-0,78%	-1,35%
H&R Block	12/01/2015	-1,14%	-0,80%	0,34%
H&R Block	13/01/2015	-1,09%	-0,21%	0,88%
H&R Block	14/01/2015	-0,03%	-0,52%	-0,49%
H&R Block	15/01/2015	-1,57%	-0,96%	0,61%
H&R Block	16/01/2015	2,53%	1,55%	-0,98%
H&R Block	20/01/2015	-0,79%	0,07%	0,86%
H&R Block	21/01/2015	1,35%	0,53%	-0,82%
H&R Block	22/01/2015	2,87%	1,64%	-1,24%
H&R Block	23/01/2015	0,68%	-0,41%	-1,09%
H&R Block	26/01/2015	1,02%	0,52%	-0,50%
H&R Block	27/01/2015	0,09%	-1,04%	-1,13%
H&R Block	28/01/2015	-0,55%	-1,50%	-0,95%
H&R Block	29/01/2015	0,81%	0,95%	0,14%
H&R Block	30/01/2015	-1,21%	-1,28%	-0,07%
H&R Block	02/02/2015	0,79%	1,37%	0,58%
H&R Block	03/02/2015	1,07%	1,67%	0,60%
Sony	01/12/2014	0,73%	-0,38%	-1,11%
Sony	02/12/2014	-0,86%	0,47%	1,33%
Sony	03/12/2014	-0,05%	0,43%	0,47%
Sony	04/12/2014	0,77%	0,02%	-0,76%
Sony	05/12/2014	0,18%	0,22%	0,04%
Sony	08/12/2014	-4,56%	-0,41%	4,15%
Sony	09/12/2014	-2,13%	0,24%	2,36%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Sony	10/12/2014	0,43%	-0,86%	-1,30%
Sony	11/12/2014	-0,24%	0,36%	0,60%
Sony	12/12/2014	-1,98%	-0,73%	1,24%
Sony	15/12/2014	-3,00%	-0,30%	2,70%
Sony	16/12/2014	0,00%	-0,20%	-0,20%
Sony	17/12/2014	3,40%	1,38%	-2,02%
Sony	18/12/2014	3,68%	1,37%	-2,31%
Sony	19/12/2014	-2,65%	0,40%	3,05%
Sony	22/12/2014	0,97%	0,32%	-0,66%
Sony	23/12/2014	0,38%	0,26%	-0,12%
Sony	24/12/2014	2,21%	0,17%	-2,04%
Sony	26/12/2014	-0,23%	0,35%	0,58%
Sony	29/12/2014	-0,47%	0,20%	0,67%
Sony	30/12/2014	-2,79%	-0,11%	2,68%
Verizon	28/04/2015	0,94%	0,07%	-0,87%
Verizon	29/04/2015	-0,16%	-0,31%	-0,15%
Verizon	30/04/2015	-0,06%	-0,71%	-0,65%
Verizon	01/05/2015	-0,06%	0,48%	0,54%
Verizon	04/05/2015	0,22%	0,11%	-0,11%
Verizon	05/05/2015	-0,85%	-0,76%	0,09%
Verizon	06/05/2015	-0,90%	-0,29%	0,61%
Verizon	07/05/2015	0,18%	0,12%	-0,06%
Verizon	08/05/2015	0,82%	0,65%	-0,17%
Verizon	11/05/2015	-0,68%	-0,32%	0,36%
Verizon	12/05/2015	-0,36%	-0,21%	0,16%
Verizon	13/05/2015	0,22%	-0,07%	-0,29%
Verizon	14/05/2015	0,48%	0,50%	0,02%
Verizon	15/05/2015	-0,36%	-0,01%	0,35%
Verizon	18/05/2015	-0,38%	0,13%	0,51%
Verizon	19/05/2015	-0,10%	-0,16%	-0,06%
Verizon	20/05/2015	0,28%	-0,09%	-0,38%
Verizon	21/05/2015	0,42%	0,07%	-0,35%
Verizon	22/05/2015	-0,58%	-0,20%	0,38%
Verizon	26/05/2015	-0,38%	-0,69%	-0,31%
Verizon	27/05/2015	0,30%	0,44%	0,13%
Mylan	12/08/2016	-0,51%	-0,22%	0,29%
Mylan	15/08/2016	0,60%	0,48%	-0,12%
Mylan	16/08/2016	-0,45%	-1,02%	-0,57%
Mylan	17/08/2016	0,76%	-0,01%	-0,77%
Mylan	18/08/2016	0,86%	0,39%	-0,47%
Mylan	19/08/2016	-1,34%	-0,44%	0,90%
Mylan	22/08/2016	-1,56%	-0,21%	1,35%
Mylan	23/08/2016	-4,76%	0,30%	5,06%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Mylan	24/08/2016	-5,41%	-1,10%	4,31%
Mylan	25/08/2016	-0,70%	-0,24%	0,45%
Mylan	26/08/2016	0,42%	-0,43%	-0,85%
Mylan	29/08/2016	0,44%	0,67%	0,23%
Mylan	30/08/2016	-1,09%	-0,40%	0,69%
Mylan	31/08/2016	-0,91%	-0,57%	0,35%
Mylan	01/09/2016	-1,04%	-0,03%	1,01%
Mylan	02/09/2016	-4,65%	0,78%	5,43%
Mylan	06/09/2016	1,08%	0,40%	-0,68%
Mylan	07/09/2016	-0,22%	-0,04%	0,18%
Mylan	08/09/2016	0,64%	-0,47%	-1,12%
Mylan	09/09/2016	-1,68%	-4,08%	-2,40%
Mylan	12/09/2016	3,61%	1,96%	-1,65%
CNN	22/08/2016	-0,36%	-0,02%	0,34%
CNN	23/08/2016	0,24%	0,30%	0,06%
CNN	24/08/2016	-0,66%	-0,57%	0,09%
CNN	25/08/2016	-0,45%	-0,04%	0,41%
CNN	26/08/2016	-0,71%	-0,16%	0,56%
CNN	29/08/2016	-0,13%	0,52%	0,65%
CNN	30/08/2016	-0,29%	-0,14%	0,15%
CNN	31/08/2016	-0,63%	-0,24%	0,39%
CNN	01/09/2016	-0,32%	0,09%	0,41%
CNN	02/09/2016	0,47%	0,59%	0,12%
CNN	06/09/2016	-0,18%	0,35%	0,53%
CNN	07/09/2016	0,42%	0,08%	-0,34%
CNN	08/09/2016	0,25%	-0,18%	-0,44%
CNN	09/09/2016	-2,42%	-2,42%	0,01%
CNN	12/09/2016	1,77%	1,32%	-0,45%
CNN	13/09/2016	-2,48%	-1,55%	0,92%
CNN	14/09/2016	-0,27%	-0,04%	0,24%
CNN	15/09/2016	-0,79%	1,00%	1,78%
CNN	16/09/2016	-1,02%	-0,36%	0,66%
CNN	19/09/2016	1,15%	0,16%	-0,99%
CNN	20/09/2016	-0,41%	-0,02%	0,39%
Macy's	20/11/2015	0,16%	-0,08%	-0,23%
Macy's	23/11/2015	3,73%	-0,37%	-4,10%
Macy's	24/11/2015	-1,02%	-0,12%	0,90%
Macy's	25/11/2015	1,89%	-0,22%	-2,12%
Macy's	27/11/2015	-0,97%	-0,26%	0,70%
Macy's	30/11/2015	-2,28%	-0,63%	1,65%
Macy's	01/12/2015	0,64%	0,45%	-0,19%
Macy's	02/12/2015	-2,26%	-1,18%	1,08%
Macy's	03/12/2015	1,40%	-1,46%	-2,86%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Macy's	04/12/2015	0,87%	1,01%	0,14%
Macy's	07/12/2015	-1,96%	-1,10%	0,86%
Macy's	08/12/2015	-0,29%	-0,80%	-0,52%
Macy's	09/12/2015	-0,75%	-0,84%	-0,09%
Macy's	10/12/2015	-0,71%	-0,15%	0,55%
Macy's	11/12/2015	-2,96%	-1,91%	1,04%
Macy's	14/12/2015	-1,06%	-0,19%	0,88%
Macy's	15/12/2015	-1,18%	0,59%	1,78%
Macy's	16/12/2015	-0,19%	0,88%	1,07%
Macy's	17/12/2015	-3,82%	-1,49%	2,33%
Macy's	18/12/2015	1,07%	-1,52%	-2,60%
Macy's	21/12/2015	0,43%	0,24%	-0,19%
Amazon	20/11/2015	1,09%	0,76%	-0,33%
Amazon	23/11/2015	1,58%	0,30%	-1,28%
Amazon	24/11/2015	-1,15%	0,68%	1,84%
Amazon	25/11/2015	0,62%	0,52%	-0,10%
Amazon	27/11/2015	-0,31%	0,46%	0,77%
Amazon	30/11/2015	-1,26%	-0,12%	1,14%
Amazon	01/12/2015	2,15%	1,59%	-0,56%
Amazon	02/12/2015	-0,45%	-1,00%	-0,55%
Amazon	03/12/2015	-1,44%	-1,44%	0,01%
Amazon	04/12/2015	0,96%	2,48%	1,52%
Amazon	07/12/2015	-0,42%	-0,86%	-0,45%
Amazon	08/12/2015	1,12%	-0,40%	-1,52%
Amazon	09/12/2015	-1,85%	-0,46%	1,39%
Amazon	10/12/2015	-0,37%	0,64%	1,01%
Amazon	11/12/2015	-3,35%	-2,16%	1,19%
Amazon	14/12/2015	2,77%	0,58%	-2,19%
Amazon	15/12/2015	0,11%	1,82%	1,71%
Amazon	16/12/2015	2,60%	2,27%	-0,33%
Amazon	17/12/2015	-0,76%	-1,49%	-0,73%
Amazon	18/12/2015	-0,97%	-1,54%	-0,57%
Amazon	21/12/2015	0,06%	1,26%	1,21%
Goldman Sachs	04/01/2016	-1,71%	-1,80%	-0,09%
Goldman Sachs	05/01/2016	-1,72%	0,10%	1,82%
Goldman Sachs	06/01/2016	-2,44%	-1,69%	0,75%
Goldman Sachs	07/01/2016	-3,07%	-2,83%	0,24%
Goldman Sachs	08/01/2016	-0,41%	-1,32%	-0,91%
Goldman Sachs	11/01/2016	1,09%	-0,26%	-1,35%
Goldman Sachs	12/01/2016	-0,01%	0,64%	0,65%
Goldman Sachs	13/01/2016	-4,06%	-3,06%	1,00%
Goldman Sachs	14/01/2016	1,51%	1,72%	0,21%
Goldman Sachs	15/01/2016	-3,58%	-2,57%	1,01%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Goldman Sachs	19/01/2016	0,78%	-0,34%	-1,12%
Goldman Sachs	20/01/2016	-1,96%	-1,30%	0,66%
Goldman Sachs	21/01/2016	-1,37%	0,59%	1,96%
Goldman Sachs	22/01/2016	3,44%	2,53%	-0,91%
Goldman Sachs	25/01/2016	-3,66%	-2,00%	1,66%
Goldman Sachs	26/01/2016	2,20%	1,78%	-0,43%
Goldman Sachs	27/01/2016	-0,47%	-1,30%	-0,82%
Goldman Sachs	28/01/2016	2,17%	0,51%	-1,66%
Goldman Sachs	29/01/2016	2,87%	2,77%	-0,10%
Goldman Sachs	01/02/2016	-1,18%	-0,11%	1,07%
Goldman Sachs	02/02/2016	-4,98%	-2,37%	2,61%
CNBC	19/10/2015	0,39%	0,02%	-0,37%
CNBC	20/10/2015	-0,02%	-0,03%	-0,01%
CNBC	21/10/2015	-0,71%	-0,70%	0,02%
CNBC	22/10/2015	0,97%	1,44%	0,48%
CNBC	23/10/2015	0,45%	1,02%	0,56%
CNBC	26/10/2015	0,32%	-0,18%	-0,51%
CNBC	27/10/2015	-1,03%	-0,35%	0,68%
CNBC	28/10/2015	0,65%	1,41%	0,76%
CNBC	29/10/2015	1,81%	-0,14%	-1,95%
CNBC	30/10/2015	-0,70%	-0,30%	0,40%
CNBC	02/11/2015	0,19%	1,30%	1,11%
CNBC	03/11/2015	-0,29%	0,39%	0,68%
CNBC	04/11/2015	-1,76%	-0,27%	1,49%
CNBC	05/11/2015	0,57%	-0,06%	-0,63%
CNBC	06/11/2015	-0,32%	0,04%	0,37%
CNBC	09/11/2015	-0,42%	-0,86%	-0,44%
CNBC	10/11/2015	0,36%	0,20%	-0,16%
CNBC	11/11/2015	-0,03%	-0,31%	-0,28%
CNBC	12/11/2015	-0,10%	-1,34%	-1,24%
CNBC	13/11/2015	-2,05%	-0,86%	1,19%
CNBC	16/11/2015	1,85%	1,42%	-0,44%
Google	17/10/2016	0,28%	-0,17%	-0,45%
Google	18/10/2016	1,82%	0,65%	-1,17%
Google	19/10/2016	0,68%	0,32%	-0,37%
Google	20/10/2016	-0,66%	-0,10%	0,56%
Google	21/10/2016	0,30%	0,04%	-0,25%
Google	24/10/2016	1,42%	0,45%	-0,97%
Google	25/10/2016	-0,86%	-0,34%	0,52%
Google	26/10/2016	-0,78%	-0,20%	0,58%
Google	27/10/2016	-0,58%	-0,31%	0,26%
Google	28/10/2016	0,27%	-0,18%	-0,45%
Google	31/10/2016	-1,18%	0,09%	1,27%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Google	01/11/2016	-0,55%	-0,56%	-0,01%
Google	02/11/2016	-2,12%	-0,65%	1,47%
Google	03/11/2016	-0,79%	-0,33%	0,46%
Google	04/11/2016	-0,14%	-0,06%	0,08%
Google	07/11/2016	2,68%	1,94%	-0,74%
Google	08/11/2016	1,24%	0,37%	-0,87%
Google	09/11/2016	-0,79%	1,13%	1,92%
Google	10/11/2016	-3,14%	0,22%	3,36%
Google	11/11/2016	-1,09%	0,08%	1,17%
Google	14/11/2016	-2,40%	0,26%	2,66%
T-Mobile	02/11/2015	1,06%	1,21%	0,16%
T-Mobile	03/11/2015	0,97%	0,42%	-0,55%
T-Mobile	04/11/2015	0,52%	-0,15%	-0,67%
T-Mobile	05/11/2015	1,49%	0,03%	-1,46%
T-Mobile	06/11/2015	-0,84%	0,12%	0,96%
T-Mobile	09/11/2015	-1,41%	-0,67%	0,74%
T-Mobile	10/11/2015	-3,97%	0,25%	4,22%
T-Mobile	11/11/2015	1,00%	-0,19%	-1,19%
T-Mobile	12/11/2015	1,52%	-1,09%	-2,61%
T-Mobile	13/11/2015	1,98%	-0,67%	-2,64%
T-Mobile	16/11/2015	-2,20%	1,32%	3,51%
T-Mobile	17/11/2015	0,74%	0,03%	-0,71%
T-Mobile	18/11/2015	-2,18%	1,45%	3,63%
T-Mobile	19/11/2015	1,10%	0,07%	-1,03%
T-Mobile	20/11/2015	1,88%	0,41%	-1,48%
T-Mobile	23/11/2015	-1,07%	0,10%	1,17%
T-Mobile	24/11/2015	0,95%	0,36%	-0,59%
T-Mobile	25/11/2015	-3,70%	0,25%	3,95%
T-Mobile	27/11/2015	-0,22%	0,21%	0,43%
T-Mobile	30/11/2015	-3,77%	-0,18%	3,59%
T-Mobile	01/12/2015	1,92%	0,96%	-0,96%
Toyota	18/11/2016	1,53%	0,01%	-1,52%
Toyota	21/11/2016	0,00%	-0,07%	-0,07%
Toyota	22/11/2016	-0,78%	-0,03%	0,75%
Toyota	23/11/2016	-0,14%	-0,01%	0,13%
Toyota	25/11/2016	2,44%	-0,03%	-2,47%
Toyota	28/11/2016	-2,45%	0,04%	2,49%
Toyota	29/11/2016	0,19%	-0,01%	-0,20%
Toyota	30/11/2016	2,12%	0,01%	-2,11%
Toyota	01/12/2016	1,10%	0,03%	-1,07%
Toyota	02/12/2016	-1,21%	-0,01%	1,20%
Toyota	05/12/2016	-0,58%	-0,06%	0,52%
Toyota	06/12/2016	-0,07%	-0,04%	0,02%

Predicted Returns vs. Actual Returns

Company	Date	Return	Predicted Return	Difference
Toyota	07/12/2016	0,33%	-0,10%	-0,43%
Toyota	08/12/2016	0,42%	-0,03%	-0,46%
Toyota	09/12/2016	1,13%	-0,04%	-1,17%
Toyota	12/12/2016	0,00%	0,02%	0,02%
Toyota	13/12/2016	-0,83%	-0,05%	0,78%
Toyota	14/12/2016	2,32%	0,07%	-2,25%
Toyota	15/12/2016	2,39%	-0,03%	-2,43%
Toyota	16/12/2016	-0,12%	0,01%	0,12%
Toyota	19/12/2016	-2,03%	-0,02%	2,01%
AOL	28/04/2015	-0,72%	0,17%	0,89%
AOL	29/04/2015	1,35%	-0,74%	-2,09%
AOL	30/04/2015	-1,51%	-1,72%	-0,21%
AOL	01/05/2015	1,75%	1,16%	-0,59%
AOL	04/05/2015	0,54%	0,26%	-0,28%
AOL	05/05/2015	-2,47%	-1,84%	0,63%
AOL	06/05/2015	-0,83%	-0,70%	0,13%
AOL	07/05/2015	-0,23%	0,28%	0,51%
AOL	08/05/2015	10,23%	1,57%	-8,66%
AOL	11/05/2015	-1,91%	-0,77%	1,14%
AOL	12/05/2015	18,62%	-0,50%	-19,12%
AOL	13/05/2015	0,49%	-0,17%	-0,67%
AOL	14/05/2015	-0,04%	1,22%	1,26%
AOL	15/05/2015	-0,22%	-0,03%	0,19%
AOL	18/05/2015	-0,18%	0,30%	0,48%
AOL	19/05/2015	-0,59%	-0,38%	0,21%
AOL	20/05/2015	0,06%	-0,23%	-0,29%
AOL	21/05/2015	-0,04%	0,18%	0,21%
AOL	22/05/2015	0,00%	-0,49%	-0,49%
AOL	26/05/2015	-0,24%	-1,67%	-1,43%
AOL	27/05/2015	-0,28%	1,05%	1,33%

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Appendix: STATA CODE

```
//=====
//===== APPENDIX: STATA CODE =====
//=====

clear
//change working directory
//*Data Preparation*//
//|(A1.0)*|//

use eventdates, clear
sort company_id
by company_id: gen eventcount=_N //|(A1.1)*|//

by company_id: keep if _n==1
sort company_id
keep company_id eventcount
save eventcount

use stockdata, clear //|(A1.2)*|//
sort company_id
merge company_id using eventcount
tab _merge
keep if _merge==3
drop _merge

expand eventcount //|(A1.3)*|//

drop eventcount
sort company_id date
by company_id date: gen set=_n
sort company_id set
```

```
save stockdata2
```

```
use eventdates, clear ///*(A1.4)*///
```

```
sort company_id
```

```
by company_id: gen set=_n
```

```
sort company_id set
```

```
save eventdates2
```

```
use stockdata2, clear
```

```
merge company_id set using eventdates2
```

```
tab _merge
```

```
list company_id if _merge==2
```

```
keep if _merge==3
```

```
drop _merge
```

```
egen group_id = group(company_id set)
```

```
save "stockdata2.dta", replace
```

```
/**Event Study**/
```

```
///*(A2.0)*///
```

```
use stockdata2.dta, clear
```

```
sort company_id date
```

```
by company_id: gen datenum=_n ///*(A2.1)*///
```

```
by company_id: gen target=datenum if date==event_date ///*(A2.2)*///
```

```
egen td=min(target), by(company_id)
```

```
drop target
```

```
gen dif=datenum-td ///*(A2.3)*///
```

```
by company_id: gen event_window=1 if dif>=-10 & dif<=10 ///*(A2.4)*///
```

```
// Change dif if event-window is different
```

```
egen count_event_obs=count(event_window), by(company_id)
```

```
by company_id: gen estimation_window=1 if dif<-30 & dif>=-120
```

```
egen count_est_obs=count(estimation_window), by(company_id)
```

```
replace event_window=0 if event_window==.
```

```
replace estimation_window=0 if estimation_window==.
```

```
tab CompanyName if count_event_obs<21
```

```
tab CompanyName if count_est_obs<90
```

```
drop if count_event_obs < 21
```

```
drop if count_est_obs < 90
```

```
drop count_event_obs
```

```
drop count_est_obs
```

```
set more off
```

```
gen predicted_return=.
```

```
egen id = group(group_id)
```

```
/**Estimating Normal Performance**/
```

```
/**(A3.0)**/
```

```
forvalues i=1(1)32 {
```

```
    l id CompanyName if id== `i' & dif==0
```

```
    reg ret market_return if id== `i' & estimation_window==1
```

```
    predict p if id== `i'
```

```
    replace predicted_return = p if id== `i' & event_window==1
```

```
    drop p
```

```
}
```

```
sort id date
```

```

gen abnormal_return=ret-predicted_return if event_window==1 ///*(A3.2)*///
by id: egen cumulative_abnormal_return = sum(abnormal_return) if dif>=-10 & dif<=10 ///
*(A3.3)*///

/**Testing for significance*/
///*(A4.0)*///

///*(A4.1)*///
//1. Cumulative Abnormal performance
sort id date
by id: egen ar_sd_i = sd(abnormal_return)
gen test =(1/sqrt(21)) * ( cumulative_abnormal_return /ar_sd_i)
list CompanyName cumulative_abnormal_return test if dif==0

//Export to Excel

export excel CompanyName event_date cumulative_abnormal_return test using "CARiT.xls" if
dif==0, firstrow(variables) replace

//Testing across all events = extra check
///*(A4.1.1)*///
reg cumulative_abnormal_return if dif==0, robust

///*(A4.2)*///
//2. Average Abnormal performance

sort dif
by dif: egen ar_sd_t = sd(abnormal_return) if dif>=-10 & dif<=10
by dif: egen AAR = mean(abnormal_return) //This is the avagere abnormal return of ALL
stocks at specific t
sort id date

```

```
gen AAR_ttest = sqrt(32) * (AAR/ar_sd_t) if dif>=-10 & dif<=10
```

```
export excel dif AAR AAR_ttest using "AARt" if dif>=-10 & dif<=10 & id==1, firstrow(variables)  
replace
```

```
///*(A4.2)*///
```

```
//3. Cumulative Average Abnormal performance
```

```
export excel CompanyName date ret predicted_return using "returns" if dif>=-10 & dif<=10,  
firstrow(variables) replace
```

```
egen CAAR = mean(cumulative_abnormal_return)
```

```
reg cumulative_abnormal_return if dif>=-10 & dif<=10, robust
```

```
// t-test and p-value is test in this case
```

```
///*(A4.3)*///
```

```
hist abnormal_return, freq bin(100)
```

```
graph save regular
```