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DEPARTMENT OF ACCOUNTING

WE THE SHEEPLE: CAN A FINANCIAL MARKET “EXPERT” TRUMP THE STOCK
MARKET?

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ABSTRACT

This thesis investigates whether “Experts” can move the stock market over the short term or the long term through their cult following and unique information spreading techniques. The specific “Expert” of study for this thesis is current U.S. President Donald Trump, specifically through his usage of Twitter. A comparison will be made of stock price movements of companies Trump has tweeted about since he was victorious in the 2016 Presidential Election on November 8th, 2016, as compared to the actual daily or weekly stock market returns as a whole.

The standard of comparison used to analyze whether or not Trump is moving the stock market will be the S&P 500. Comparing company price movements after Trump has tweeted about them to the S&P 500 performance will help to analyze whether Trump’s tweets have a profound effect on the valuation of the companies he complements/critiques or if these firms’ share prices are simply moving with the market. To test these research questions, data will be collected over a series of Trump tweets from November 8th, 2016 to November 16th, 2018. A price comparison will be made one day and one week after the tweet was made.

Overall, it was found that Trump did influence the companies he made a negative tweet about in the one-day return following the tweet. However, this effect of negative tweets was very short term and did not differ significantly from the S&P 500 over the longer term, as the one-week later results illustrate. There was no statistically significant evidence to suggest that Trump moved the market in the daily or weekly returns for companies he complemented on Twitter. These results suggest that Trump may be influencing a large portion of the market that is trading on noise (especially negative tweets) more than anything else and his opinions do not have a strong impact on the markets outside of a very short term timeframe.

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Chapter 1

Introduction

Prior to the 2008 Great Recession in the United States, society placed a great deal of faith in government and financial institutions. For example, in the years leading up to the recession, based on the Federal Reserve's and the financial institutions' "Expert" guidance, most people believed that the housing market and financial markets would never crash, with many models predicting that housing prices would increase by 6-8% in perpetuity (Shostak, 2009). Unfortunately, these "Experts" were incorrect, resulting in 50% price corrections and great losses to the uninformed public who put their faith in the information provided by the "Experts".

Given this disastrous financial outcome, an important question to ask oneself is, what makes someone an "Expert"? While "Expert" is a relative term, some people do not garner this acclaim due to the accuracy of their predictions and their knowledge of their fields of expertise, but simply because their opinions are followed by millions of people/investors. This does not necessarily mean they are good analysts. Instead, they are deemed "Experts" due to their popularity, as measured by their number of followers.

For example, a theme throughout the campaign of President Donald J. Trump was his promise to "Make America Great Again". It was through this phrase that Trump helped instill confidence in his supporters that he was the person that could create change in United States, building a very close trust with his base. Through this trust, Trump garnered support from his followers and others that he was an "Expert" who had a plan to improve the financial and social quality of life of his supporters by changing government policies on many things, such as trade

deals, markets, and the economy in general. This paper attempts to measure how much people believe Trump to be an “Expert”.

As President of the United States, Trump has the capability to get his messages across to many people in a very short time frame. Trump currently has over 55 million followers on Twitter alone, the 16th most followers in the world (November, 2018). Additionally, it is clear that Trump’s messages are seen, as his tweets consistently get as many as 100,000 or more favorites each. Trump’s number of followers and frequency of daily tweets have increased as his presidency has progressed, suggesting that this is his main platform of communication and that people consistently rely on his Twitter page for news.

During the 2016 US presidential election, political scientists Gross and Johnson noted, “Social media have emerged as an important weapon in the campaign messaging arsenal, with Twitter taking center stage. When it comes to newsworthy events such as a presidential campaign... tweets themselves have become news and thus, essentially free advertising for candidates. For the first time, all candidates in a large field are active on Twitter and have used the platform to provide running commentary, allowing us to witness the emergence of negativity in real time,” (Gross and Johnson, 2016). It is very clear that Trump established a cult following through his unique usage of Twitter that made people feel as though they identified with Trump. This leaves us with the question of the degree to which Trump’s followers act on his expression of opinions and other statements on Twitter.

Using stock price performance relative to the broad market index, this paper analyzes perceived “Expert” Donald Trump’s success in moving the markets through the social media platform, Twitter. Is President Trump truly a guru? Or does President Trump have no clue? In order to define financial market activists and to define investment expertise, this paper first

introduces academic literature for insight into theories that are currently used to explain market activity. In the following section, a description of the methodology used and test study conducted is provided. Finally, results and conclusions based on these results is provided.

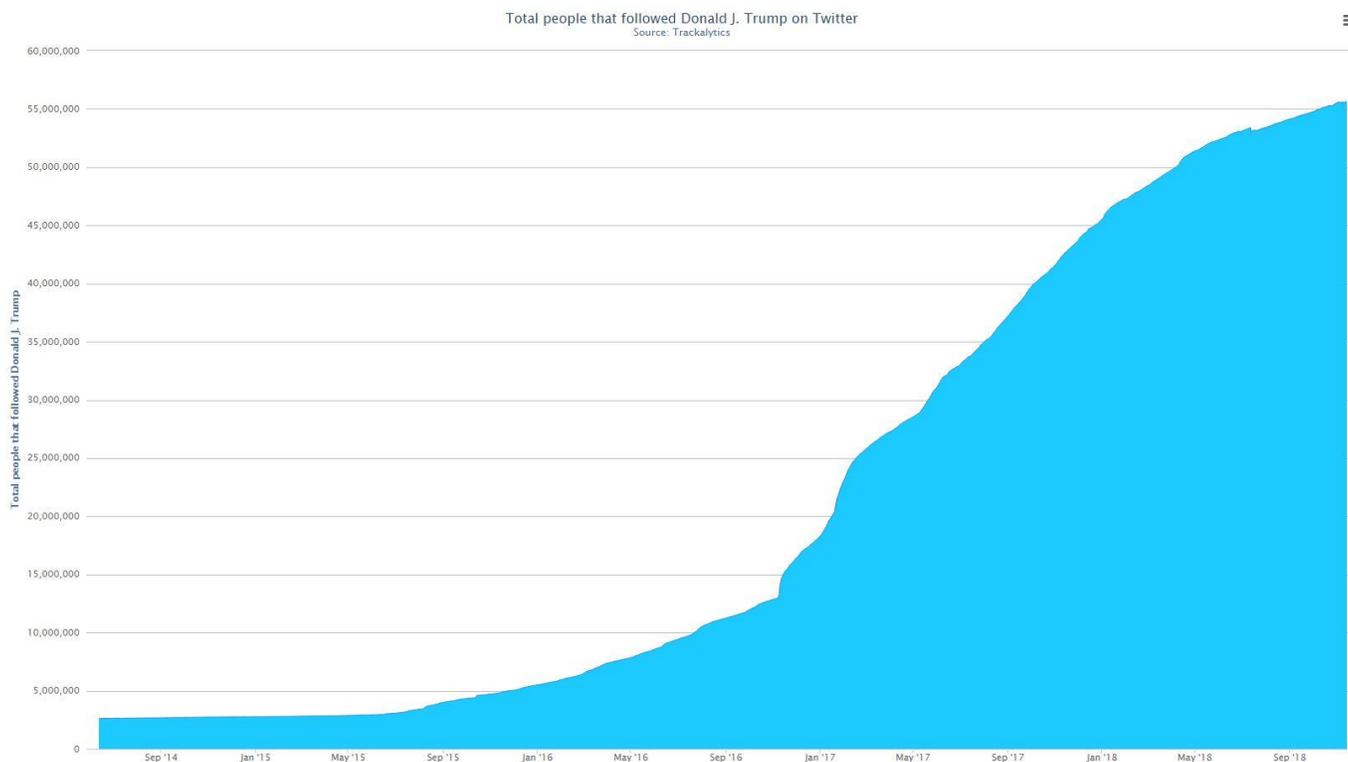


Figure 1. Number of Trump Followers on Twitter

<https://www.trackalytics.com/twitter/profile/realdonaldtrump/>

Chapter 2

Literature Review

“If you say it right, almost anything can be good... If you say it wrong, almost anything can be bad.” -Bryan Caplan, Economist/Professor at George Mason University (Freakonomics Radio Podcast We the Sheeple, 2012)

While Professor Caplan’s statement is somewhat cynical, recent history has suggested that it is largely correct. As technological capabilities have exponentially increased across the world, more and more people have the abilities to be influenced and follow “Expert” opinions on the stock market. While many people believe that readily available information can help educate the public and help them make generally smart investment decisions, this is not always the case.

2.1 Perfect Information vs. Noise

A common problem in today’s society is a lack of trustworthy and truthful information. Fischer Black (1986) opens one of his most cited research papers, aptly titled “Noise”, by saying, “Noise makes financial markets possible, but also makes them imperfect.” Noise traders trade on what they believe is information, though there may be little consensus about this information’s validity. Black describes how there are two types of traders, information traders and noise traders. It is the noise traders that create these imperfect markets, “People who trade on noise are willing to trade even though from an objective point of view they would be better off not trading,” Black notes. Noise traders allow for market liquidity and price movement in the markets, thus creating money making opportunities for information investors from these imperfect markets (Black, 1986).

Black's research helps to illustrate how certain facts and information are hard to decipher as true or false for some people. Believing that one person is an "Expert" in a field may lead to someone trusting such information when they should not. Nonetheless, people continue to trade off this information, further leading to improper pricing. With an increase in the amount of trading platforms available to make these trades, there is a higher opportunity in today's society to be exposed to improper information and pricing of underlying assets from trading off of misinformation.

2.2 Valuation Model

Expanding upon this idea, it is useful to note that in different valuation models, people not sharing similar opinions act upon information differently. For example, in the Capital Asset Pricing Model (CAPM), some assumptions need to be made to determine the appropriate risk premium, calculated as return on market – risk free rate. The CAPM provides a formula that calculates the expected return on a security based on its level of risk. The formula for the capital asset pricing model is the risk-free rate plus beta times the difference between the return on the market and the risk-free rate. The risk-free rate is the expected return on an investment that is assumed to have no risk, such as a Treasury Note. The beta is the correlation of said investment to the overall current market risk. Additionally, the risk premium is the expected return on the market for said investment minus the risk free rate. Or, stated in equation form:

$$\text{Expected Return} = r_f + \beta(r_m - r_f)$$

r_f = risk free rate

β = Beta

r_m = return on the market

As mentioned, the risk premium varies across investors, as its valuation could be dependent on how old the investor is, where they went to school, or even what the person who taught them CAPM believes. In a sense, there are too many variables for people to apply CAPM and other valuation models the same way, thus making some of these valuations less accurate and causing variance from person to person. Additionally, CAPM applies assumptions about stock price returns that are by no means always true, such as the assumption of normality of returns and the non-existence of skewness and kurtosis.

2.3 How Markets Process Information

In George Akerlof's research paper "Lemons", a similar type of information phenomenon known as adverse selection is also explored. Using the example of the automobile industry, Akerlof describes a model that assumes that there are only four types of cars (new, used, good, "lemons"). It is through these four types that an equilibrium is established in the marketplace. Given incomplete information and the presence of inferior cars in the market, the market for the quality cars is harmed because the sellers cannot differentiate between good cars and lemons, resulting in quality cars being priced out of the market (Akerlof, 1970).

Similar to Black's research, Akerlof helps to illustrate how misguided information can lead to inefficiencies in the markets. It is very difficult to decipher in the present day what is credible and discreditable information. Additionally, it can be hard to tell what sources are and are not reliable regarding certain information. For example, more often than not, someone will not want to report something that contradicts their original reporting and thus would make them look bad. Additionally, a source will be the first to report something if it makes themselves appear correct or more credible.

Louis Bachelier first paved the way for using mathematics to value the prices of stocks in times of uncertainty (Bachelier, 1900). Each of Bachelier's models helped to advance mathematical modeling in finance, but came at a time before trading noise was as prevalent in the markets, further influencing deviations from what these investments true values may be. What was once assumed to be efficient markets may not be as efficient in the present day due to technologically advanced and faster information gathering and spreading techniques throughout the world.

Eugene Fama's 1965 dissertation further suggests that stocks often exhibit "fat tail" distribution properties, implying that extreme movements in stocks are more common than typically expected, even under conditions of normality (Fama, 1965). Fama's research helped to imply that large increases and decreases in stock price are not all that uncommon and can be expected. Fama also helped introduce the Efficient Market Hypothesis. This hypothesis explained how investors have differing viewpoints on the efficiency of markets, which include each of the following:

- Strong form efficiency theory refers to the idea that stocks reflect all information available. This includes public information, as well as private information not yet disclosed to the general public.
- Semi strong form efficiency theory is one notch below this, as this theory refers to the idea that only publicly available information is reflected into the prices of the stocks.
- Weak form efficiency theory reflects the idea that only past prices are reflected into the stock prices, suggesting that technical analysis cannot be used to assist in valuing the stock.

There is no definitive consensus as to which theory is correct. However, as already mentioned, Caplan's earlier statement brings up a very important point: the process by which the public interprets information about investments can be ambiguous. How does someone perceive publicly available information and how is this built into the stock prices? Additionally, what is considered publicly available information and what is considered the inaccurate information put out to the public for them to believe is true, when much of it can be considered false? In this regard, it is necessary to consider how the Efficient Market Hypothesis addresses the problem of noise.

2.4 Market Efficiency vs. Bias

The concept of confirmation bias, as first suggested by Peter Wason, may have some effects in markets (Wason, 1960). As previously mentioned, if someone sees an "Expert" make a statement confirming their belief, they will be much more likely to follow through with their belief about the markets, without considering the validity and accuracy of their

beliefs. Confirmation bias could in turn influence the short term and long term valuation in markets as a whole, even though they are not necessarily valued properly. Relating back to how many of Trump's followers seem to identify with him, seeing Trump state an opinion may help to confirm their thoughts about a company, even though no actual facts support his opinion one way or another. This in turn may lead to incorrect price valuations.

To test whether investors, including Trump's followers and the broader market at large, rely on his investment insights, Trump's tweets will be tested to see if the tweets significantly affect the market by causing abnormal stock returns, using a financial methodology known as an event study. An event study is a statistical method to measure the impact of a specific event (in this case a tweet) on the value of a firm. Illustrating cases in which tweets generated abnormal returns helps to explain how markets may not always behave as expected and the degree to which these unexpected results have occurred in the market place, given an anticipated result as compared to the actual results (Brown and Warner, 1980). Abnormal returns can be calculated by determining the expected return given past performance and testing whether future stock price movements significantly deviated from this historical performance.

Putting all of this together, it can be assumed that a statement made by a flawed "Expert" may result in confirmation bias. This confirmation bias can be measured in an abnormal returns test, to illustrate the amount of deviation between a firm's stock price movement and its expected returns. This test will be further investigated in this research paper.

Chapter 3

Methodology

This research paper will explore the depths of Trump's influence on the stock markets and how well his opinions fare against the S&P 500. As already mentioned, Trump was selected as an "Expert" based on several different criteria, including a high level of following from the investing community, his large number of followers on various social media platforms, as well as his unique opinion-sharing style through these platforms.

3.1 Sample Selection

A sample size of 29 positive or negative tweets about 18 different companies was used for this study. The tweets were gathered from November 8th, 2016 to November 16th, 2018. The criteria used for selecting Trump's tweets are

1. The tweet occurred during non-trading hours (9:30-4:00 PM)
2. The tweet was posted after 4:00 PM on a Monday but before 9:30 AM on a Friday

By using these criteria, the risk of intraday tweet-effects being split over different days is eliminated. To control for contradictory tweeting, the sample size will be split by running two different tests, one for the positive tweets and one for the negative tweets. Additionally, if Trump were to make multiple tweets (positive or negative) about a company within the same week timeframe, only the first tweet would be used for this study. This will help to eliminate mid-week tweet effects from the original tweet of interest.

Out of the sample size of 29 different tweets, 17 of these tweets were positive. Of these 17 different tweets, there were 11 unique companies of interest mentioned. Additionally, there were 12 different negative tweets about companies. Of these 12 negative tweets, there were 8 unique companies of interest mentioned.

3.2 Significance Tests

There will be two tests conducted for this study. A measurement of the cumulative abnormal return (CAR) for companies that Trump has tweeted about negatively and a separate calculation of the CAR for companies that Trump has tweeted about positively. CAR can be defined in this study as the sum of the actual returns over the time period of interest for the stock, minus the expected return of the stock over that time period based upon the actual return in the market for that duration.

$$\text{CAR} = \Sigma \text{Return of Stock} - \text{beta} * (\text{actual return in market})$$

Each of these return measurements were calculated over a one-day and one-week time period. This way, there can be a study on whether there was a short term movement and whether such market reactions persist over a longer period of time.

3.3 Pre-Study Hypothesis

The initial expectation is that there will be no difference between the expected return and the actual return (Ho: expected return = actual return). This hypothesis holds true for both the positive and negative tweet testing. A negative tweet will have a point of interest that measures how much the stock decreased following the tweet and a positive tweet will have a point of

interest that measures how much the stock increases since the tweet. In essence, there are two separate tests to control for the sentiment of the tweets, measuring the degree in which the stock moves up in reaction to positive tweets and moves down in reaction to negative tweets.

A T-Test was conducted on each tweeted stock to compare its price movement to its expected daily and weekly returns, where the expected return is calculated by multiplying the firm's beta coefficient times the results of the daily and weekly returns in the S&P 500 for that same time interval. A T-Test is used to determine if the two datasets are significantly different from each other. The T value is found by calculating the average abnormal returns of a dataset (in this case the expected stock return based on the firm's beta multiplied by the actual market return for the time period of interest minus the actual return for the stock) multiplied by the square root of the sample size, with this product divided by the standard deviation of the abnormal returns. It is important to keep in mind that a one-tailed T-test will be conducted, as the interest of the study is in testing whether Trump moves the company's stock in the direction his tweet suggests it should move.

To incorporate market movement for the day or week, CARs based on the expected daily or weekly return on the markets were calculated. Based on these measures, T-tests were later applied to determine statistical significance, based on a level of statistical significance of 95%. The stocks expected return, multiplied by the stock's last 3-year monthly beta (via Yahoo Finance) provides the expected return, with abnormal returns calculated in comparison to these results.

Chapter 4

Results

As illustrated in Appendix A, results were significant for the one-day returns focusing on negative stock tweets at the 99% confidence level, far exceeding the required 95% confidence. More specifically, a T-Test Value of -3.248 was found based on the daily abnormal returns. Based on these results, there is statistically significant one-day downward movement in a firm's share price when Trump tweets something negative about a company. A range of CAR values for this test varied .62% to -2.76%, with a standard deviation of .83%. A negative CAR reflects that Trump is moving the market based on the connotation of his negative tweet.¹

However, looking beyond the one-day negative tweet results, data was not significant for the one-week negative tweets, suggesting that Trump's influence on the market is very short lived. More specifically, as shown in Appendix B, a T-Test Value of -1.196 was found based on the weekly abnormal returns for companies Trump negatively tweeted about. The range of values was much wider here, from 4.48% to -25.5%, resulting in a standard deviation of 7.85%.

In stark contrast to the one-day response to negative tweets, the positive tweet results were insignificant one day and one week after Trump's tweets. In fact, as illustrated in Appendix C and Appendix D, the markets reacted in the opposite direction of what they needed to be for Trump's tweets to have statistical significance. For the one-day positive tweet returns, the average abnormal return was actually -.13% (it would be positive if Trump's positive tweets had an impact) with a standard deviation of 1.00%. Abnormal returns ranged from -3.11% to

¹ A negative tweet about Comcast on November 29, 2017 was removed from the sample of overserved tweets due to an abnormal amount of trading and skewed results due to their changed pledge on net neutrality (Brodkin, 2017)

1.23%. The T-value was -.498. For the one-week positive returns, the average abnormal return was -.30 with a standard deviation of 3.81. Abnormal returns ranged in value from -7.69% to 8.31%. The T-value was -.28.

From this information, it can be concluded that Trump may move the market when tweeting something negative about a company for its one-day return. However, this cannot be said for any of the other returns measured in this study.

Chapter 5

Conclusion

The null hypothesis was that a firm's stock price would move in line with the markets daily and weekly returns. Specifically, for one-day returns on the negatively tweeted stocks, it was found that Trump significantly moved the markets, thus disproving the initial hypothesis. However, this cannot be said for the weekly return of the negatively tweeted stocks or the daily and weekly returns for the positively traded stocks. These findings support the idea of market noise temporarily influencing the markets for the short term of negatively tweeted companies.

A possible explanation for why Trump's negative tweets greatly impact the market for the very short term is because investors believe that Trump may influence policies that negatively impact that company. Conversely, when Trump complements a company, there is less likely to be any sort of change that impacts that company. This helps to further explain the results of higher significance for the negative tweets.

A noteworthy limitation of this study was its small sample size. A smaller-than-ideal sample size was used to ensure that there would be no lapping of intraday trading, therefore giving an outlier a greater effect. Due to the intraday trading restriction, the sample size was less than 30 and therefore inconsistent with the Central Limit Theorem. However, to ensure that it was truly the one-day and one-week returns, this restriction was implemented.

Possible ideas for further studies include whether specifically positive or negative tweets have a higher correlation to moving the market if voiced by different "Experts". Other "Experts" of interest with large followings could include Jim Cramer through television, Warren Buffett

through value investing, Carl Icahn through hostile takeover and David Tepper through distressed company investments. A specific list of popular “Experts” and their success against the S&P 500 over their investing careers is charted in Figure 3 below.

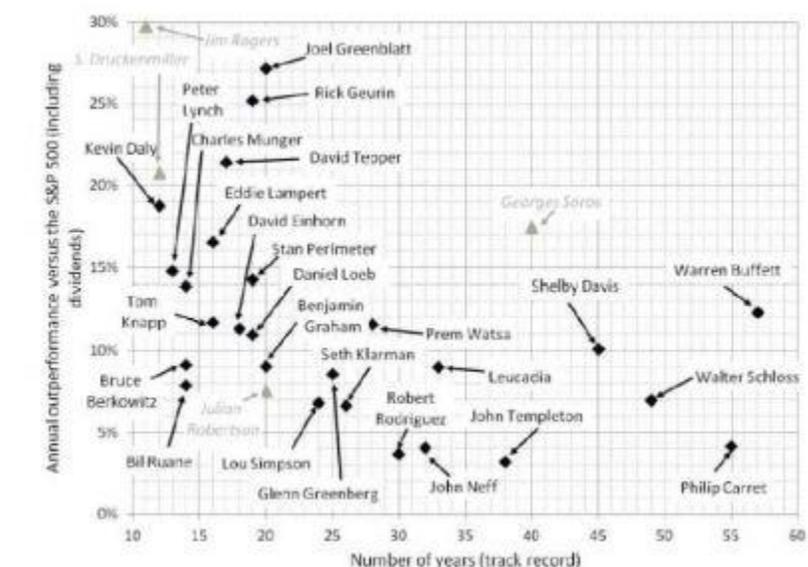


Figure 2. "Experts" vs. the S&P 500

Similar to Trump, these “Experts” are not always correct in their evaluations. In 2009, then Daily Show host Jon Stewart aired a featured segment in which Cramer was invited onto the show to defend himself for supporting the purchase of the Bear Stearns stock, when shortly after Cramer’s recommendation the stock plummeted to two dollars per share. Bear Stearns was later bought out by JP Morgan Chase. Initially, Cramer defended himself for his suggestion of the purchase of the stock at 62 dollars per share. However, by the end of the interview, Cramer admitted he made a mistake, noting that any time the market moves in the opposite direction of what he says, he has made a mistake and explains how that is a part of the job. Examples like this suggest that other “Experts” may be an interesting further study.

Additionally, evaluating price performance by the hour may better illustrate the impact of the effect of Trump's tweeting on the market. Another idea to investigate is whether changes in Trump's approval ratings have an effect on how strongly his tweeted companies outperform the markets. A final promising area of study is to measure Trump's number of followers at the time of each tweet to see if his follower count correlates with the abnormal return following his positive and negative tweets.

Appendix A

Negative Tweets One-Day Return

<u>Company</u>	<u>Beta</u>	<u>Date of Interest</u>	<u>Abnormal Return</u>
Boeing	1.69	12/6/2016	-0.52%
Lockheed Martin	0.77	12/23/2016	-1.37%
Amazon	1.81	6/28/2017	-0.21%
Amazon	1.81	7/25/2017	-0.44%
Amazon	1.81	8/16/2017	-0.72%
Amazon	1.81	12/29/2017	-0.46%
Amazon	1.81	3/29/2018	-1.38%
Nike	0.77	9/5/2018	0.62%
Facebook	0.7	9/22/2017	-0.38%
Comcast	1.43	7/25/2018	-1.21%
Google	1.43	8/28/2018	-0.87%
Twitter	0.43	7/26/2018	-2.76%
Average Abnormal Return			-0.75%
Standard Deviation			0.83%
T Table Value			-
			3.248884599

Appendix B

Negative Tweets Week After One-Day Return

<u>Company</u>	<u>Beta</u>	<u>Week After One-Day Return</u>	<u>Abnormal Weekly Return</u>
Boeing	1.69	12/13/2016	-2.18%
Lockheed Martin	0.77	12/30/2016	-0.38%
Amazon	1.81	7/5/2017	-1.54%
Amazon	1.81	8/1/2017	-4.59%
Amazon	1.81	8/23/2017	-1.01%
Amazon	1.81	1/5/2018	-0.12%
Amazon	1.81	4/5/2018	-2.60%
Nike	0.77	9/12/2018	4.48%
Facebook	0.7	9/29/2017	-0.67%
Comcast	1.43	8/1/2018	6.38%
Google	1.43	9/4/2018	-3.58%
Twitter	0.43	8/2/2018	-25.50%
Average Abnormal Return			-2.61%
Standard Deviation			7.85%
T Table Value			-1.196876571

Appendix C

Positive Tweets One-Day Return

<u>Company</u>	<u>Beta</u>	<u>Date of Interest</u>	<u>Abnormal Return</u>
Ford	0.74	11/18/2016	-0.75%
Ford	0.74	3/28/2017	1.12%
Ford	0.74	1/25/2017	0.83%
United Technologies	1.04	11/30/2016	-0.75%
Exxon	0.81	12/13/2016	1.23%
Exxon	0.81	3/7/2017	-0.14%
Merck	0.98	7/21/2017	-0.46%
Corning	1.24	7/21/2017	0.49%
Google	1.43	7/19/2018	-0.57%
Apple	1.27	4/25/2018	0.20%
Apple	1.27	1/18/2018	0.29%
Pfizer	0.84	7/11/2018	0.01%
Pfizer	0.84	7/21/2017	-0.15%
Pfizer	0.84	7/19/2018	-0.46%
Novartis	0.86	7/19/2018	0.71%
Sinclair	1.41	7/24/2018	-3.11%
Tribune	1.13	7/24/2018	-0.69%
Average Abnormal Return			-0.13%
Standard Deviation			1.00%
T Table Value			0.498628874

Appendix D

Positive Tweets Week After One-Day Return

<u>Company</u>	<u>Beta</u>	<u>Week After One-Day Return</u>	<u>Abnormal Weekly Return</u>
Ford	0.74	11/25/2016	0.54%
Ford	0.74	4/4/2017	-1.37%
Ford	0.74	2/1/2017	-2.28%
United Technologies	1.04	12/7/2016	-0.96%
Exxon	0.81	12/20/2016	-1.10%
Exxon	0.81	3/14/2017	-1.89%
Merck	0.98	7/28/2017	1.91%
Corning	1.24	7/28/2017	-7.69%
Google	1.43	7/26/2018	4.88%
Apple	1.27	5/2/2018	8.31%
Apple	1.27	1/25/2018	-6.05%
Pfizer	0.84	7/18/2018	-0.04%
Pfizer	0.84	7/28/2017	-1.12%
Pfizer	0.84	7/26/2018	0.68%
Novartis	0.86	7/26/2018	2.43%
Sinclair	1.41	7/31/2018	-3.84%
Tribune	1.13	7/31/2018	2.51%
Average Abnormal Return			-0.30%
Standard Deviation			3.81%
T Table Value			-0.281757128

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February 2016-August 2017

- Mentor for 30+ incoming PSU freshmen transitioning to college
- Assisted in budgeting, organizing, and designing educational activities for students
- Tutored students in Management Information Systems (MIS), Statistics and English

Lifeguard, Science Park Recreation Association

May 2011-September 2015

- Certified as Red Cross lifeguard, recertified every two years
- Extensive background in pool safety and loss control, including training in cardiopulmonary resuscitation (CPR) and automated external defibrillator (AED)
- Assisted my supervisor in managing the daily operations of the pool
- Trained as conductor for Emergency Action Plan (EAP) procedures

Volunteer Assistant Track Coach at State College Area High School

March 2017-May 2017

- Volunteered as a track coach at my high school following my PwC internship
- Training group I coached included four state runner ups, one fifth place state finish, one seventh place state finish, and four All Americans

Honors:

- Penn State Interfraternity Council Scholarship Award Winner (2014)
- Centre Daily Times Snyder Award Winner (2014): Regional newspaper award for community service, athletic, and academic achievement
- Proficient with SAS, Microsoft Word, PowerPoint, and Excel
- Big Ten XC/Track and Field Distinguished Scholar
- Two-time Pennsylvania Interscholastic Athletic Association state champion for track