The Impact of Twitter News on Stock Price Returns

by

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Budapest, 16 June 2020

Signature

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Abstract

This study aims at establishing whether the spikes in the Twitter activity of the US 116th Congress representatives mentioning a certain company's name signify abnormal returns for the mentioned firm's stock price. The scraped Twitter dataset is used for the identification of the event days, while the rest of the analysis is performed on the stock price return dataset. The results of the conducted event study reveal that the effect of Twitter news on the stock price returns is inconsistent, as the abnormal returns for the identified events are not significant across all the chosen companies. However, a closer look at the sentiment expressed the days before and after the events reveals that whenever the sentiment of the tweets is consistently negative or positive the days around the event, the abnormal returns are found to be statistically significant and mainly correspond to the sign of the sentiment.

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Chapter 1

Introduction

The recent technological revolution resulted in widespread access to the Internet and an extraordinary flood of data and news in real time, which changed dramatically the way social media is looked upon nowadays. The social media outlets, such as Twitter, Reddit, etc. are slowly becoming primary sources of timely information due to their functions of live streaming as the events in the "offline" world are happening. News media outlets are decentralized by their nature, which results in difficulties to track all the events in their chronological order. Twitter, on the other hand, provides accurate information about any tweet made by any account, which makes it possible to track down the timeline of the news.

1.1 Motivation

Twitter.com is an online social networking platform, which has currently over 330 million monthly active users (as of 2019). Although initially, it started out as a social media outlet for people to express their thoughts in under 140 characters, it slowly grew into a "hub" of information, where the traditional news sources and media outlets also have their accounts (handles) that they use. In addition, there are tweet collections from news outlets available (labeled as Moments) that provide highlights for certain events. It is important to note that more and more companies choose to reveal their news on Twitter accounts over any other social networking platforms. For example, the International House of Pancakes (IHOp) first took to Twitter to announce breaking news on its re-branding: temporary switch to IHOb, where the "b" stands for burgers, to promote a new line-up of beef patties. This news quickly became trending on Twitter, and fast-food chains such as Burger King and Whataburger joined the "roast" party of the company by changing their names to "Pancake King" and "Whatapancake". People all over Twitter called this change a branding fail, proposing that "b" in the name should stand for "bankruptcy". In a matter of hours, the hashtag "#IHOb" was the number one trending topic in the Twitter in the United States, and people who never knew about IHOp in the first place learnt about the existence of the company.

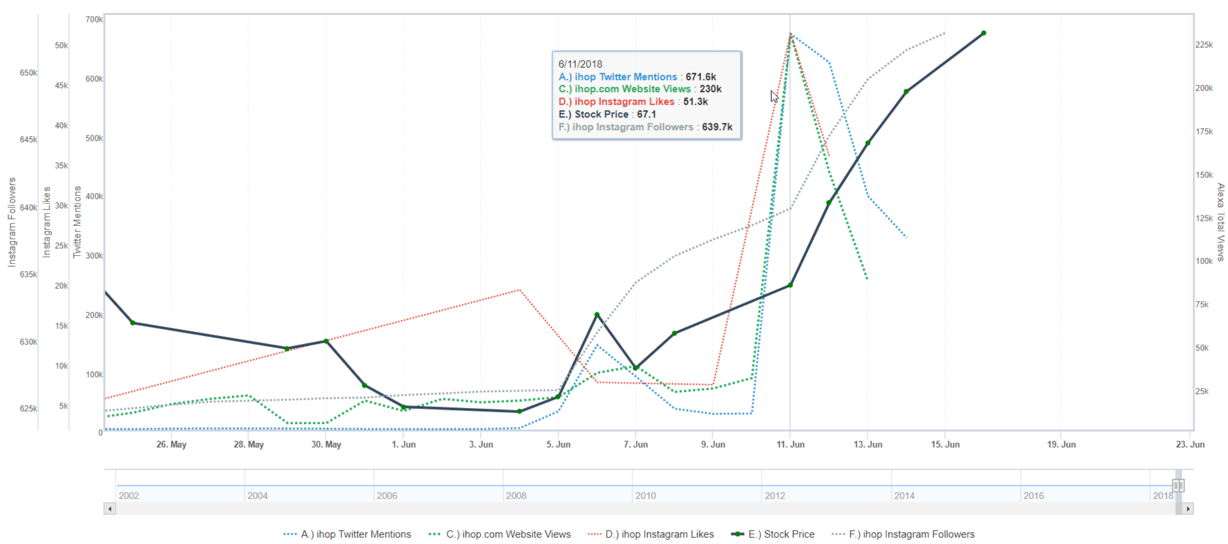

Figure 1.1: Social Media Response to IHOp

The announcement of the re-branding took place on 11th of June, and from the figure above [1] , you can see skyrocketing numbers from the social media channels. Twitter mentions (blue), the official website views (green) and Instagram numbers (likes: red, followers: gray) peaked on the day of the announcement, as well as the stock price ($DIN) had a steady increase for at least 5 days afterwards. The stock price increased by over 18% after the announcement. According to IHOp chief marketing officer Brad Haley, the name game worked as IHOp initially sold four times more than they had done previously. I believe that is why more and more influential people, businesses, institutions, etc. prefer expressing their opinion and news via their Twitter accounts. This is the main reason why I choose Twitter over other microblogging platforms for this study.

Twitter has also become one of the main platforms for politicians to share their ideological and political beliefs and agitate for them. 2016 and 2020 United States Presidential election campaigns are one of the most prominent examples, during which the Twitter was exploding with live reactions to the developments. According to PEW Research Center survey (December 2018), among US adults with public accounts, 26% follow former President Barack Obama's account, 19% follow President Donald Trump's accounts. According to the same survey, 21% of those adults follow at least one member of the US Congress. Worth noting that they are twice as likely to follow Democratic legislator than Republican one.

The politicians are using the platform not only for sharing their thoughts on different events but also reporting on the news in the country, economic performance indicators, political rally results, and in general any relevant information regarding not only the whole country but their specific states and districts. While expressing their opinion about certain company or reflecting upon news relevant for a company, the stock price of the mentioned firm can fluctuate based on the volume of the tweets and/or general sentiment of the news.

[1] Adapted from Sentieo by Shah, Alap (2018). Retrieved May 20, 2020, from this link.

For example, if Walmart decides to close down 10 of their department stores in a certain district, the representative from the US Congress is most likely going to express his/her thoughts on that matter in the tweets. The closure of stores is expected to be reflected in the stock prices of the company, and although its announcement in Twitter would have not been the primary trigger for the stock price change, the news will almost immediately be on the platform too, thus, can be considered as Twitter news. Another example can be when politicians tweet about their stances on a certain company based on their beliefs. And if the opinions expressed in the tweets are persuasive and shared or the audience reach of those tweets is large enough to affect traders' decision making, it will inevitably affect stock prices of the mentioned company. Thus, I believe, there is potential relationship between the news expressed in politicians' tweets and the stock prices of tagged companies.

1.2 Scope and Focus

Numerous studies have questioned the assumptions of the Efficient Market Hypothesis, which states that stock prices follow a random walk, and they are determined by new information, i.e. news, rather than past trends. Kavussanos & Dockery (2001) found that the stocks traded in the Athens Stock Exchange are informationally inefficient, i.e. the past stock prices contain useful information about future price movements. Another study, conducted by Gruhl, Guha, Kumar, Novak & Tomkins (2005) showed that early indicators of upcoming news can be obtained from social media outlets, such as online postings, feeds, etc. They find that online postings successfully predict spikes in the sales rank of books, meaning that social media can be helpful in identifying the information relevant for trader's decision making. However, to my knowledge, the existing literature does not address the connection between politicians' tweets and stock price movements. Hence, I intend to look at whether the tweets made by US political figures have an impact on the traders' decision making, which leads to the changes in the stock price returns of the companies mentioned in those tweets.

The main question posed in this research is whether the spikes in the Twitter activity of the US 116th Congress representatives mentioning a certain company's name signify abnormal returns for the mentioned firm's stock price. The scraped Twitter dataset is used for the identification of the event days, while the rest of the analysis is performed on the stock price return dataset. The results of the conducted event study reveal that the effect of Twitter news on the stock price returns is inconsistent, as the abnormal returns for the identified events are not significant across all the chosen companies. However, a closer look at the sentiment expressed the days before and after the events reveals that whenever the sentiment of the tweets is consistently negative or positive the days around the event, the abnormal returns are found to be statistically significant and most of the times correspond to the sign of the sentiment.

This thesis is organized as follows. Chapter 2 summarizes the previous literature relevant to the questions posed in this study. Chapter 3 presents the data scraping, organizing, and cleaning process, and the tools used throughout those processes. Chapter 4 sets out empirical methods based on the data and methods used in the relevant literature. In Chapter 5 results are presented, and in Chapter 6 follows the discussion, drawn conclusions and limitations of the research.

Chapter 2

Stock Market. Theory and Evidence

Stock market is a dynamic and non-linear process by its nature, and the prediction of it has always been an important topic in the financial world, as an accurate prediction of the stock market future movements makes it possible to hedge against market risks. The approaches and methods used for the prediction of the fluctuations have significantly changed since the advancements in technology. As news channels have gradually shifted their main focal point to the Internet, the researchers refocused their attention to online news media outlets ("online" world) for identification of the new information relevant for the stock price prediction. Thus, I would like to organize the discussion of the existing theory according to the approaches implemented in them. I will briefly present the keystone studies exploring stock market behavior and concentrate more on the existing literature exploring "online" world (website, social platform, micro-blogging app, etc.).

2.1 Historical Background

The Efficient Market Hypothesis (EMH) has been one of the cornerstone theories on market behavior. According to the idea of the theory, capital market is considered to be efficient if prices in the market fully reflect available information. In his groundbreaking study, Fama (1965) introduced the notion of an efficient market, defining it as a competitive market, where the random nature of the prices is explained by its convergence to the fundamental value. He argued that as the price variations were nearly independent, random walk was a good approximation of the price behavior. Samuelson (1965), on the other hand, explained the randomness of the stock prices by the competition between investors. In contrast to Fama, he was attempting to explain the phenomenon of randomness, rather than taking it as a secondary issue. Both of the studies have concluded that stock prices follow random walk, as new information is unpredictable. Nevertheless, numerous studies have since shown that market prices can be predicted to some degree.

Qian & Rasheed (2007) showed in their study that with appropriate use of machine learning classifiers it is possible to achieve prediction accuracy of 65 percent, meaning stock prices do not follow random walk and can be predicted with the right choice of features. With the technological advancements, the number of features relevant for the stock price prediction has significantly increased, and the next section is reflecting upon studies exploring the relationship between online news and stock market.

2.2 "Online" World

As the world is getting more and more computerized and networked, the power and influence of the Internet grows excessively. As a result of these changes, the number of factors affecting systemic risk in the financial system has grown, thus, making it more complex to predict the realization of it. With the advent of the new technologies and online media outlets, the approaches and the variety of tools used for the identification of the new information (i.e. news) on the Internet relevant for stock price prediction have increased and advanced. Thus, the techniques used for conducting studies aimed at the exploration of the relationship between web news and stock market performance vary across the literature. With the development of search engine traffic [2] it became possible to not only track but also predict the behavior of users. Bordino et al. (2012) reflected upon this topic in their study, finding that web search queries can predict stock market volumes. The aim of the study was to identify early warnings of financial systemic risk solely based on the search query volume. They showed that the daily trading volumes of stocks traded in Nasdaq 100 and daily volumes of queries related to that stock are correlated. They also found that the peaks of trading can be anticipated by search query volume by one day or in some cases even more days in advance. The authors concluded that the query volume change is driven by the collective yet uncoordinated activity of users.

Da, Engelberg and Gao (2011) also used search query tools in their study aimed at explaining investor behavior. They proposed a new and direct measure of investor attention by exploring search frequency in Google (Search Volume Index: SVI). The authors pointed out traditional proxy measures of investor attention such as volume, news, abnormal returns, etc. and showed that the newly constructed index is correlated with existing proxies and captures investor attention in a more timely fashion. The results indicated that an increase in SVI predicts higher stock prices in the next two weeks.

Another approach commonly used in the literature is identifying news on social media platforms. With the rapid spread of social media, it became easier to communicate the announcements, events, opinion, etc., given that the reach of those outlets gradually outnumbered the traditional news communication channels, such as newspapers, journals,

[2]The number of request submitted by users to search engines on World Wide Web (WWW)

even website postings. The exploding popularity of Twitter resulted in the platform being in the epicenter of the research due to its increasing audience reach and almost real-time feed. One of the pioneers in that field were Zhang, Fuehres and Gloor (2011) and Bollen, Mao and Zeng (2011) with their studies exploring whether Twitter mood predicts the stock market. Both of the papers looked at the correlation of the mood and stock market indicators and found that there is a significant comovement of those indices.

Mao, Wang, Wei, and Liu (2012) advanced the aforementioned studies by including only tweets that mention Standard & Poor's 500 (S&P 500) stocks and investigating whether they are correlated with S&P 500 stock indicators (stock price and traded volume). The preliminary results demonstrated that the volume of the tweets is correlated with the specific stock market indicator, meaning that at the stock market level, including Twitter data can be useful for identification of the future stock price movements.

All the mentioned papers have not used filtering on the Twitter dataset users, i.e. they have used all the relevant tweets of any public account on the platform. However, in my study, I would like to concentrate on the tweets made by politicians, as I believe that Twitter became extremely relevant in current politics. A study by Tumasjan, Sprenger, Sandner, and Welpe (2010) revealed that Twitter's popularity within the political sphere is not a new emergent phenomenon. In the research carried out in 2009, they showed that Twitter is indeed used extensively for political deliberation. The results indicated that the political sentiment expressed in the tweets goes in line with the politicians' "real-life" political positions, which means that the content of the tweets correctly reflects the offline situation.

Given the widespread use of the platform among political figures, this study aims at establishing whether the tweets made by US politicians have an impact on the stock price returns of the companies mentioned in those tweets. The next section carefully presents the data collection steps and guides through the tools used in the preparation process.

Chapter 3

Data

The data used for this research is divided into two main parts: Twitter data and stock price data. Twitter data is obtained for all the 116 $^{\text{th}}$ United States Congress representatives from a period of 18 months between October 2018 and April 2020. Since the research aims to establish whether there is an impact of Twitter news on the stock price returns of the tagged companies, after careful pre-processing, five of the most-mentioned companies are chosen for the stock price return analysis. The companies selected for the study are Amazon.com, Inc. (AMZN), Apple Inc. (AAPL), The Boeing Company (BA), Wells Fargo Company (WFC) and Walmart Inc. (WMT). In the subsequent sections, all the data collection steps are thoroughly presented.

3.1 Twitter Data

Twitter is a social networking platform, where the users communicate and interact through the messages knows as 'tweets', thus the first step in the data collection process is the scraping of 116th US Congress representatives' tweets. Collectively there are

435 seats, however, some of them have left the office and others substituted the vacant places, therefore, I collected the names and Twitter usernames (referred to as 'handles' onwards) of all the people who have been serving in the office for the aforementioned period of time. Overall, Twitter data for 438 accounts was scraped using two packages in Python: Tweepy and GetOldTweets3, which is an improvement fork for original GetOldTweets package, with a final number of tweets obtained just under half a million (445,000 tweets). Table 3.1 below displays representatives with the highest number of tweets in the period of my interest. As one can observe, 8 out of 10 most active users are representatives of the Democratic Party.

State	Name	Twitter Handle	Number of tweets
WA-07	Pramila Jayapal (D)	@RepJayapal	4866
AZ-05	Andy Biggs (R)	@RepAndyBiggsAZ	3999
MD-05	Steny H. Hoyer (D)	@LeaderHoyer	3515
VA-08	Donald S. Beyer, Jr. (D)	@RepDonBeyer	3430
FL-26	Debbie Mucarsel-Powell (D)	@RepDMP	3394
FL-10	Val Butler Demings (D)	@RepValDemings	3347
NY-13	Adriano Espaillat (D)	@RepEspaillat	3139
NE-02	Don Bacon (R)	@RepDonBacon	3005
MA-03	Lori Trahan (D)	@RepLoriTrahan	2979
NY-12	Carolyn B. Maloney (D)	@RepMaloney	2979

Table 3.1: Top 10 Active Representatives

Subsequent to the scraping process, I carried on with data cleaning. The first step of the data preprocessing is a sentiment score calculation. As the collection of tweet texts itself does not provide any context for the overall mood, calculation of the sentiment score for each of the tweets provides context by measuring the tone and emotions expressed in them. I used the VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon and rule-based sentiment analysis tool, which is specifically designed for computation of sentiment expressed in social media outlets. It does not require any training data, generalizes to multiple domains, and most importantly quantifies the extent of positivity and negativity expressed in the tweets, which is highly useful in the case of collected data. The next step of the data preprocessing involved dropping all the tweets made on the weekends and Bank holidays, as the stock market cannot immediately react to the Twitter updates. However, I assume that the sentiment score expressed in the tweets during the weekend has subsequent effect on the investors the next working day. Thus, I calculate the average of the sentiment score of the weekend/holiday and the next working days' tweets as an overall score for the next business day.

In Figure 3.1, you can see the top 2000 words mentioned in the tweets, which were identified after punctuation signs and stopwords removal and tokenization. The most frequently used words include "today", "house", "people", etc. All the aforementioned top

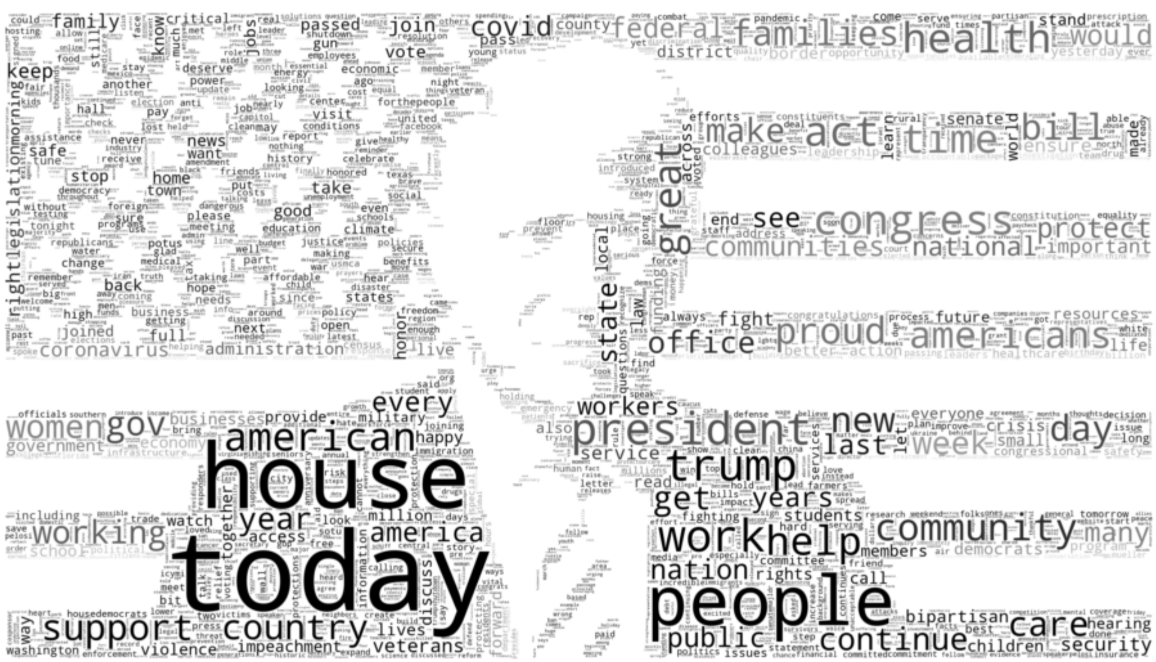

Figure 3.1: Top 3000 Words used in Representatives' Tweets

words are expected, as the datasets includes tweets made by members of the United States House of Representatives. The representatives are frequently reflecting on the discussions taking place on the same day, thus the word "today" is the most mentioned one.

For extraction of the most popular tags and mentions, I used 're' (Regular expression operations) package from Python. Figure 3.2 displays the top 20 mentions in the tweet texts. As we witnessed earlier, Democrats are relatively more active on the Twitter platform, thus the Twitter account for democrat representatives is on the second place. Figure 3.3 represents top 20 tags used in Representative's tweets. #COVID19 is the most frequently used hashtag, although it is quite a recent topic, it quickly captured worldwide attention because of its fatality statistics.

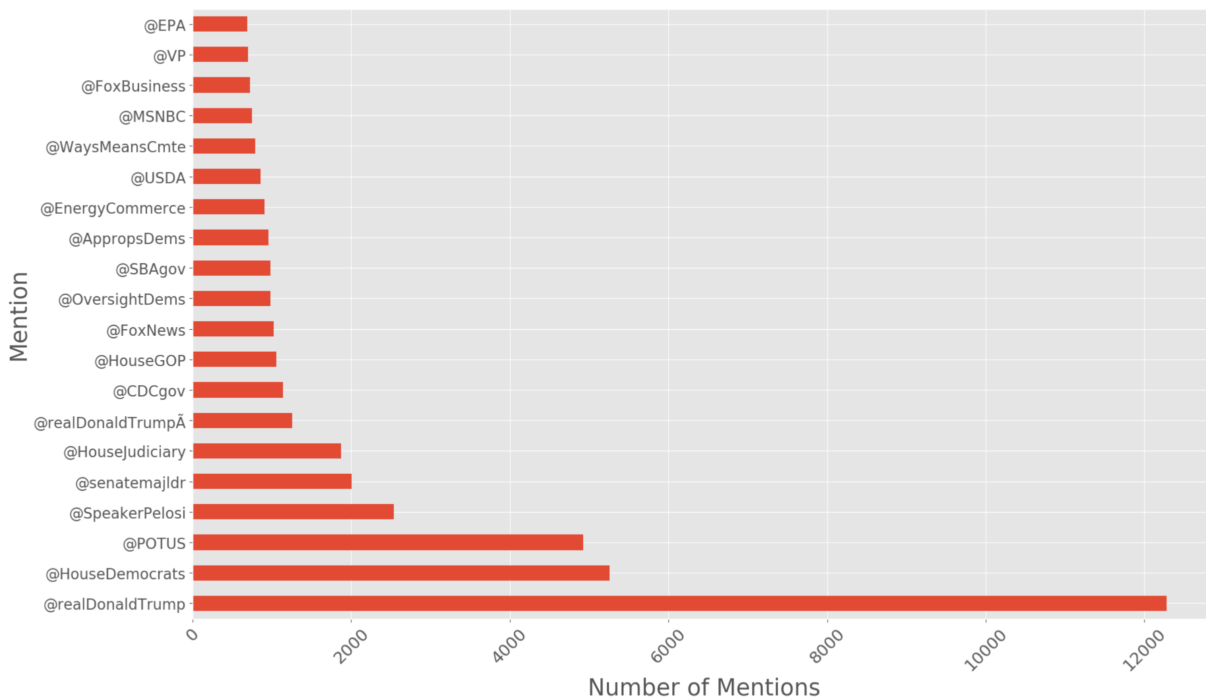

Figure 3.2: Top 20 Mentions in Representatives' Tweets

One of the most crucial steps of data pre-processing is detecting the tweets, which have tags and mentions of publicly traded companies. For completion of that stage, I chose two main techniques: Named Entity Recognition and phrase matching. NER is an information extraction tool, which locates and classifies the names of entities in text into pre-defined categories. In the case of collected data, I will use named entity recognizer with SpaCy (package in Python) and choose the organization as the category for the classification. The

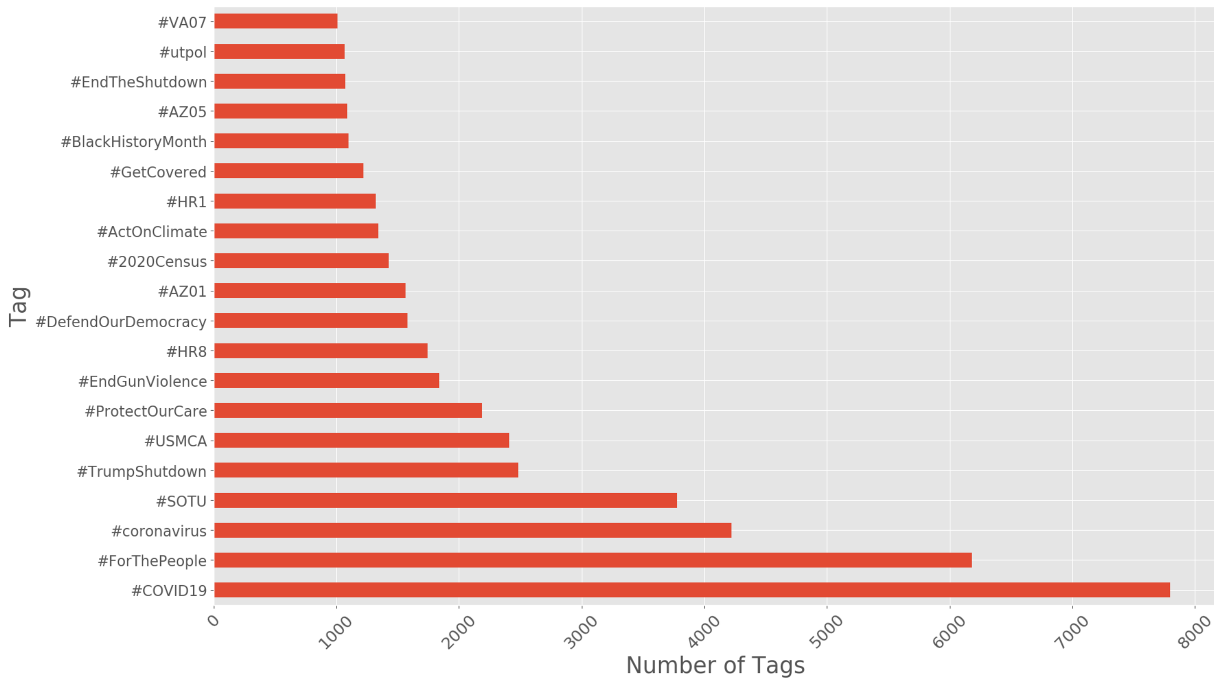

Figure 3.3: Top 20 Tags in Representatives' Tweets

recognizer works best with training data, and as the collected data does not contain any labels, the categorization is noisy.

The next step for the more efficient location of mentions, I create a separate dataset with the US Fortune 500 companies (2019) that are publicly traded (495 firms). As in tweet text, the users may mention the short versions of the company names, or only their Twitter handle, or stock price symbol, the created dataset contains all the possible variations of the names. Using 're' (Regular expression operations) package in Python, the mentioned companies are identified and their stock symbol is added to the existing Twitter dataset. After the aforementioned steps are completed, 15000 firms have been identified to be mentioned in the tweets. In addition to all the steps, a manual cleanup of the data is performed, as some of the entities are wrongly classified because of the special characters in the name. It is important to note that before entity recognition and matching, the tweet text is not preprocessed to avoid eliminating necessary punctuation signs and symbols, which might be part of the company's name.

The next step is the identification of the companies for the stock price return analysis. Five companies are chosen based on the number of mentions in the tweets and the industry. Both Amazon.com, Inc. and Apple Inc. are the giants in technological innovation, The Boeing Company is the world's largest aerospace company, Wells Fargo & Company is world's fourth-largest bank by market capitalization and the fourth largest bank in the US by total assets, and finally, Walmart Inc., an American multinational retail corporation, is the world's largest company by revenue, according to the Fortune Global 500 list in 2019. The aforementioned companies are presented in Table 3.2 along with the number of mentions in the tweets.

Company Name	Stock Symbol	Mentions
Amazon.com, Inc.	AMZN	280
Apple Inc.	AAPL	190
The Boeing Company	BA	188
Wells Fargo & Company	WFC	113
Walmart Inc.	WMT	110

Table 3.2: Companies Selected for the Study

For event identification, a few additional steps are required. I calculate the number of tweets for each company per each day for the period of my interest and then choose the dates where the number of tweets mentioning a specific company lies outside 95% and 99.7% confidence intervals ($mean + 2st.dev$ and $mean + 3st.dev$ correspondingly). See Table 3.3 with the identified event dates, where dates in bold represent events falling outside 99.7% confidence interval.

The final step in the data preparation process is the collection of the stock price data, which is presented in the next section.

Company	Stock Symbol	Event Date
Apple Inc.	AAPL	1/29/2019
Apple Inc.	AAPL	**10/10/2019**
Apple Inc.	AAPL	**3/31/2020**
Apple Inc.	AAPL	**4/6/2020**
Amazon.com, Inc.	AMZN	10/2/2018
Amazon.com, Inc.	AMZN	**2/14/2019**
Amazon.com, Inc.	AMZN	**8/22/2019**
The Boeing Company	BA	5/15/2019
The Boeing Company	BA	**10/30/2019**
Wells Fargo & Company	WFC	**3/12/2019**
Wells Fargo & Company	WFC	3/10/2020
Walmart Inc.	WMT	8/5/2019
Walmart Inc.	WMT	**9/4/2019**

Table 3.3: Selected Companies and Event Days

3.2 Stock Data

After identification of the companies and events, the next step would be obtaining stock price data. In addition to the companies identified, I also collect stock price data for the S&P 500 index, which will serve as a market portfolio indicator for further analysis. I use the "fix-yahoo-finance" package from Python to download the financial data from January 2018 to April 2020. The period covered by stock data is larger than for the Twitter data,

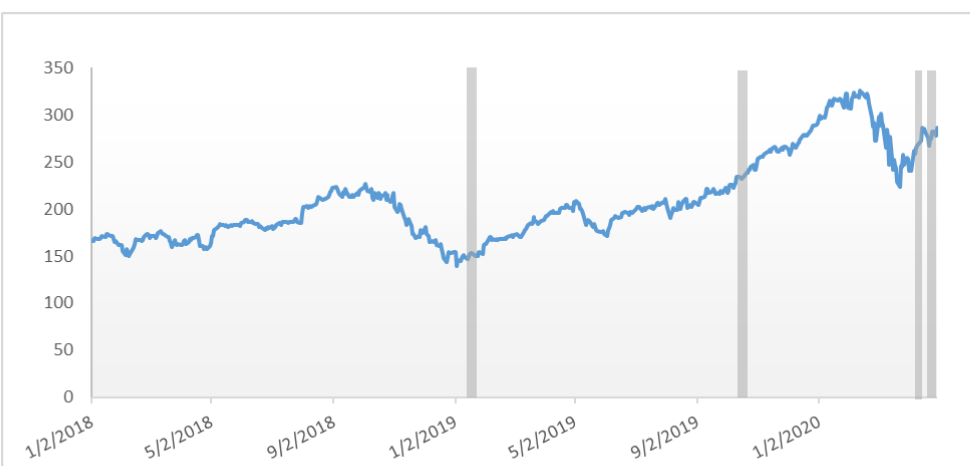

Figure 3.4: Apple Inc. Closing Price

as in the event study the data for the observance period should also be included. The figure depicts Apple Inc. stock price for the two-year period. The shaded gray areas represent previously identified events with a two-day window.

After stock price data collection, I proceed to the calculation of the stock price returns, which will be described in the upcoming chapter. Based on the dates and company name I add to the financial data the corresponding cumulative sentiment score, which will be used later in the analysis. This concludes the data collection process, and the next section concentrates on the discussion of the methodology used.

Chapter 4

Empirical Strategy

The event study statistical method is chosen for assessing the impact of Twitter news on the stock price returns, as it enables quantifying the impact of an event on the abnormal returns of the firm. For carrying out the estimation, some assumptions need to be considered. First, there are two types of investors/traders: noise traders and rational arbitrageurs. Noise traders act randomly once they obtain new information, while rational arbitrageurs hold Bayesian beliefs. Both of the traders are assumed to be risk-averse. This goes in accordance with the Efficient Market Hypothesis, meaning that after obtaining relevant news the noise traders sell or buy stocks to rational arbitrageurs based on the sentiment of the news.

Secondly, I assume that the spikes in the number of tweets mentioning a certain company reflect the news relevant for investors' decision making. This assumption is necessary for conducting event study, as the days of the events are identified by the spikes in the number of tweets in a day. The last assumption would be that investors/traders obtain their information from the Twitter accounts used for the scraping. As the congressmen/congresswomen are representatives elected to a two-year term serving the people of a specific congressional district, I assume that news potentially affecting the stock market will be reflected in the tweet releases. The high popularity of politicians' Twitter accounts in the United States leads to the conclusion that the information reflected there is available to the traders.

Given the fast pace nature of Twitter, the response of the market is expected to be fast, thus the event window is considered to be short. The Figure 4.1 displays timeline for an event study. The estimation period is chosen to be 200 days prior to the event window,

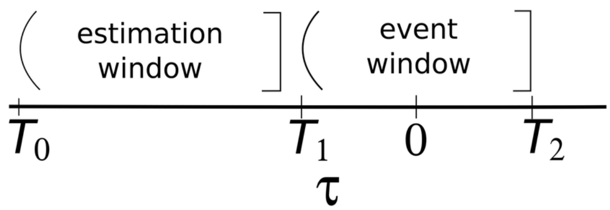

Figure 4.1: Event Study Timeline

and the event window covers a 5-day period: two days prior to the event, the day of the event (marked by 0) and two days after it. I expect news to be reflected in Twitter on some occasions later than the actual date, given that most of the politicians may react to the news and tweet about it post-fact, thus, I include a two-day lag to the event window.

As I am interested in the movements of stock price returns to the announcement of the news, I would like to exclude the movements related to the market, that is why the S&P 500 index is included as an indicator for market movements. Returns for companies and the S&P 500 index is calculated on a daily basis. The stock price return for a company i at time t is calculated in the following way:

$$\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

where P is the adjusted closing price (adjusted for splits and dividends). The next step is the calculation of Abnormal Returns (AR) using the OLS single-factor market model.

The returns calculated prior are used in the single-factor market model for the estimation of parameters, which are further used for the calculation of abnormal returns.

In the market model it is assumed that the returns follow a single-factor market model:

$$R_{i,t} = \alpha_i + \beta_i * R_{m,t} + \epsilon_{i,t}$$

where $R_{i,t}$ is the return of the stock of observation i (e.g. firm) at time t, $R_{m,t}$ is the return of the market portfolio indicator (the S&P 500 index) at time t and $\epsilon_{i,t}$ is the error term (a random variable) with expectation zero and finite variance. One of the main assumptions is that the error term is uncorrelated to the market return and also company return. The regression coefficient β_i is a sensitivity measure (i.e. responsiveness) of the company stock price return to the market return. Note that both α and β are estimated for each event of each company using the data points from the estimation window. These values are consequently used for the calculation of abnormal return using the following formula:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i * R_{m,t})$$

The next step would be the calculation of Cumulative Abnormal Return (CAR) for each event for each firm, which is the sum of the abnormal returns during the event window $(a : b)$, where a and b represent respectively the number of days before and after the event. For example, the length of the event window $(2 : 2)$ is 5 days: 2 days prior to the event, the day of the event and two days after it. The Cumulative Abnormal Return for each company per each event is calculated in the following way:

$$CAR_{i,j} = \sum_{t=a}^{b} AR_{i,t}$$

Thus, the event study time frames for a specific event in this analysis are defined as following.

Event day: T_0

Estimation period: $T_{-205:-6}$

Event windows: $T_{(a:b)}$, where the event windows are (1 : 1), (2 : 2), (3 : 3),(5 : 5).

Finally, both $AR_{i,t}$ and $CAR_{i,j}$ are tested for statistical significance using $t-test$, where the standard statistics are:

$$t_{AR} = \frac{AR_{i,t}}{\sigma_{AR}/\sqrt{n}}$$

$$t_{CAR} = \frac{CAR_{i,j}}{\sigma_{CAR}/\sqrt{n}}$$

$AR_{i,t}$ and $CAR_{i,j}$ are abnormal return and cumulative abnormal return for each company per each event, σ_{AR} and σ_{CAR} are the standard deviation and cross-sectional standard deviation of abnormal returns obtained from the single-factor market model, and n is the sample size. The next section will present the results of the estimations and subsequent discussion.

Chapter 5

Main Results

The first step in the evaluation process is the estimation of the abnormal and cumulative abnormal returns for each event window per each company. Table 5.1 displays the estimation results for the Apple Inc. for each of the selected four events. In the Appendix you can find the results for all the companies: Table 6.1 presents estimation results for Amazon, Table 6.2 for Boeing, Table 6.3 for Wells Fargo and finally Table 6.4 for Walmart.

Estimates/Events	1/29/2019	10/10/2019	3/31/2020	4/6/2020
Intercept	0.000	0.001	0.003	0.002
Slope (beta)	1.434	1.509	1.174	1.141
Standard Error	0.013	0.012	0.010	0.011
R squared	0.559	0.604	0.822	0.834
CAR(0,1)	0.038	0.012	0.011	-0.007
CAR(-1,1)	0.041	0.010	-0.002	-0.006
CAR(-2,2)	0.057	0.020	-0.019	-0.033
CAR(-3,3)	0.047	0.008	-0.042	-0.048
CAR(-5,5)	0.072	0.007	-0.097	-0.003
AR(0)	-0.008	0.003	0.014	0.005

Table 5.1: Event Study Estimations for Apple Inc.

As it can be seen from the table, the estimated beta coefficients for all the four events are well above 1, which indicates higher stock price volatility compared to the overall market. The inconsistency in the numbers for each of the events is explained by the difference of the estimation periods. Closer look at the results reveals that both Apple and Amazon estimated beta coefficients are always greater than one for all the events. This is explained by the nature of the industry these companies operate in, i.e. technology and internet retail. High growth technology driven firms are considered to be relatively risky, thus, have comparatively higher betas. The success of such companies relies heavily on the innovation and creativity, something that is not correlated with the overall market performance.

Table 5.2 displays the statistical tests of all the return indicators for all the companies. Event dates in bold indicate the peaks in the tweet volume, i.e. the number of tweets referring to a specific company was laying outside 99.7% confidence interval.

Event date	Stock symbol	AR	$CAR_{(1:1)}$	$CAR_{(2:2)}$	$CAR_{(3:3)}$	$CAR_{(5:5)}$
1/29/2019	AAPL	-0.60	3.11*	4.36*	3.60*	5.49*
10/10/2019	AAPL	0.26	0.81	1.73*	0.72	0.60
3/31/2020	AAPL	1.37*	-0.22	-1.86*	-4.00*	-9.36*
4/6/2020	AAPL	0.47	-0.57	-3.10*	-4.58*	-0.33
10/2/2018	AMZN	-1.44*	-2.89*	-4.61*	-4.00*	-3.26*
2/14/2019	AMZN	-0.42	-2.90*	-1.92*	-2.42*	-3.59*
8/22/2019	AMZN	-0.68	0.30	0.16	-0.26	-2.55*
5/15/2019	BA	0.01	1.25	0.76	0.69	0.42
10/30/2019	BA	-0.65	-0.04	0.27	0.08	1.80*
3/12/2019	WFC	-0.38	-1.40*	-0.08	0.53	1.82*
3/10/2020	WFC	2.93*	-4.25*	-12.87*	-11.24*	-10.77*
8/5/2019	WMT	-1.86*	-0.86	-0.56	-2.06*	-5.36*
9/4/2019	WMT	0.40	-0.18	-0.86	0.98	0.47

Table 5.2: T-test analysis
Test statistics calculated at 80% confidence interval

As it can be observed from the table above, the abnormal returns for most of the events are non-significant, while the more lags are included in the calculation of cumulative abnormal returns the more significant they get. However, I believe the significance of cumulative abnormal returns (CAR) for further lags cannot be considered reliable, as the more days are included, the returns (calculated with adjusted closing price) that were originally negative on the day of the event turn positive and vice versa. Overall the results do not show any consistent pattern of significance, yet the sentiment scores may provide more insight, which will be discussed in the following chapter.

Chapter 6

Conclusion and Discussion

The previous section presented the results of the event study analysis, which did not reveal significant consistent relationship between the Twitter news and stock price returns of the mentioned companies. Moreover, including lags of the abnormal returns in the calculation of the cumulative estimate proved to be unreliable as the effects have cancelled each other out on multiple occasions.

Closer look on the sentiment data revealed that for the events, where the sentiment score was consistently negative or positive several days before and after, the abnormal returns were found to be statistically significant.On the other hand, when the sentiment expressed in the tweets were inconsistent, the abnormal returns were not statistically significant. This observation was performed by first comparing the cumulative compound score (CCS) to the cumulative absolute compound score (CACS) for given days. Secondly, I looked closer on the individual sentiment score data to validate the results. For example, October 2, 2018 is identified as an event for Amazon.com Inc. and when looking closer at the sentiment data around that day, I discover that the sentiment score for the surrounding days is consistently negative. For February 2, 2019, which is also identified as an event for

Amazon.com Inc. (and the number of tweets is considerably higher than for other events) the compound sentiment data shows positive value, however, looking closer at the scores of individual tweets mentioning the company it is revealed that the sign of the sentiment scores is not consistent. As the cumulative number is considered, the individual effects are cancelling each other out. August 5, 2019 is identified as an event for Walmart and closer look at the individual sentiment scores reveals consistent negative sign for all the tweets mentioning Walmart at the day of the event, and from the estimates we can see that abnormal returns are statistically significant and negative for that day. Nevertheless, the number of events and observations is very limited, thus, the conclusions cannot be generalized without appropriate statistical estimation on extended dataset.

One of the main subjects that need to be discussed is the definition of the "Twitter news" and what falls under that category. I believe, the news shared by the politicians can be roughly divided into three main categories:

- news happening in the offline world that are reflected in their tweets
- politicians tweet their opinion or stance on a certain company, institutions, etc. and because of the audience reach, many people start forming opinions and expressing them
- the companies, institutions, etc. choose to inform company related news on their user pages, and the politicians instantly retweet or share their opinion on the subject matter

In this study I do not differentiate between these categories, as all the tweets mentioning relevant companies are included in the analysis. For further improvement of the study, I would like to consider only the tweets falling under the second category. That way I can see whether the "artificially" created news on Twitter have an actual impact on the stock prices of the mentioned companies.

Apart from the mentioned ones, there are several limitations to the study. For example, the events are identified based on the isolated days on which the number of tweets per day mentioning the company peaked. Keeping in mind that the entity recognition and matching was not completely accurate (for example, on multiple occasions the company names appeared to be part of a link, which was irrelevant to the company itself), the choice of the event days can be questioned.

It is also crucial to note that when choosing the US 116th Congress representatives as a sample, considerable portion of potentially relevant information shared by influential politicians is excluded from the analysis. As an improvement to this research, the tweets of former presidents, current president, the President's cabinet, speakers, etc. should also be included in the analysis. In addition, Twitter results using search 'key' as the names of the companies or their stock price symbols (for example, $AMZN) should also be included along with most important political news media outlets' Twitter accounts (CNN, CBS, Fox News, etc.).

In spite of the limitations mentioned above, this rudimentary algorithm sheds light on the potential relationship between the tweets volume and the stock price returns of the companies mentioned in those tweets. It also provides enough evidence for further exploration of the association between tweets' sentiment and stock price returns.

Appendix

Figure 6.1: Amazon.com, Inc. Closing Price

Figure 6.2: The Boeing Company Closing Price

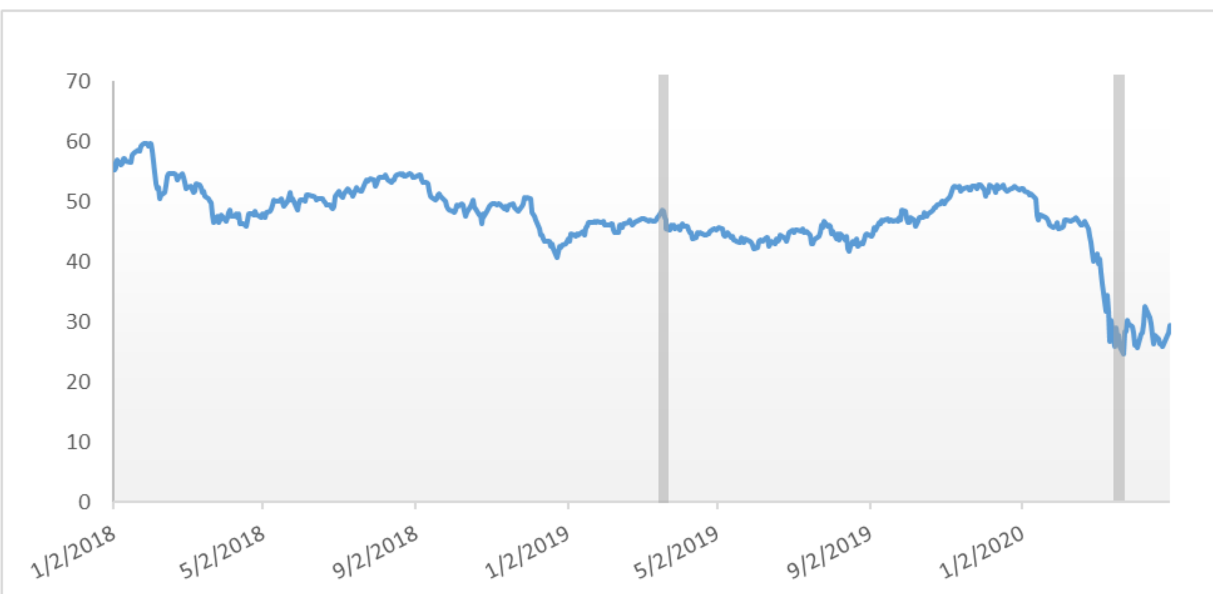

Figure 6.3: Wells Fargo & Company Closing Price

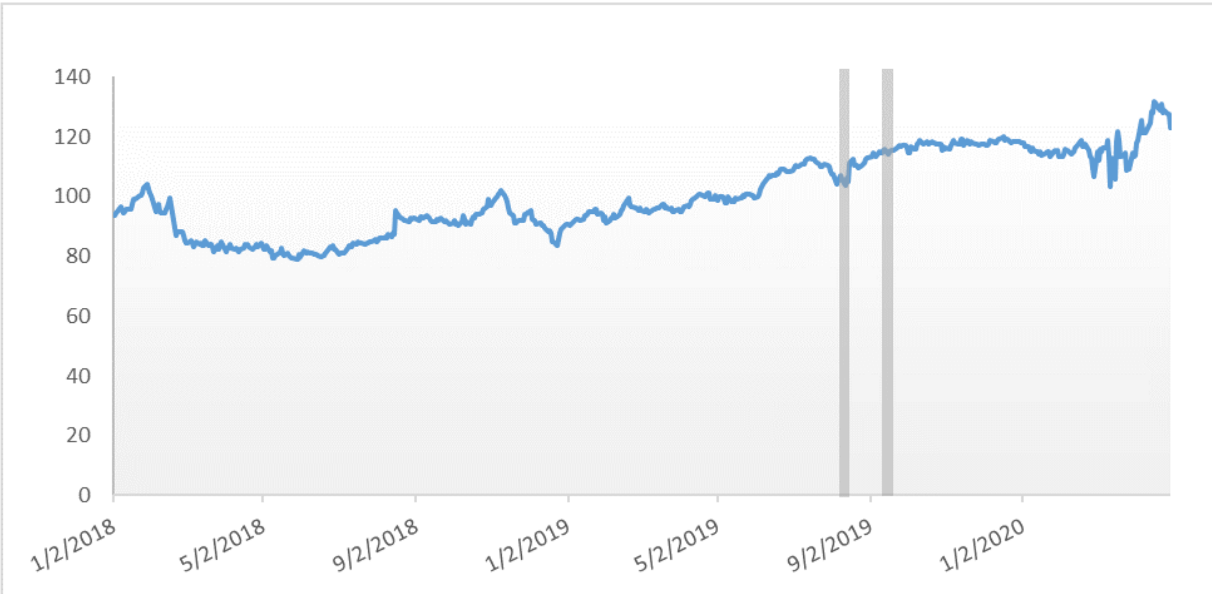

Figure 6.4: Walmart Inc. Closing Price

Estimates/Events	10/2/2018	2/14/2019	8/22/2019
Intercept	0.002	0.000	0.000
Slope (beta)	1.186	1.902	1.735
Standard Error	0.013	0.014	0.013
R squared	0.412	0.655	0.647
CAR(0,1)	-0.031	-0.036	0.006
CAR(-1,1)	-0.037	-0.041	0.004
CAR(-2,2)	-0.059	-0.027	0.002
CAR(-3,3)	-0.051	-0.034	-0.003
CAR(-5,5)	-0.041	-0.050	-0.034
AR(0)	-0.018	-0.006	-0.009

Table 6.1: Event Study Estimations for Amazon.com, Inc.

Estimates/Events	5/15/2019	10/30/2019
Intercept	0.000	0.000
Slope (beta)	1.267	0.943
Standard Error	0.015	0.017
R squared	0.419	0.170
CAR(0,1)	0.012	-0.025
CAR(-1,1)	0.019	-0.001
CAR(-2,2)	0.012	0.004
CAR(-3,3)	0.011	0.001
CAR(-5,5)	0.006	0.030
AR(0)	0.000	-0.011

Table 6.2: Event Study Estimations for The Boeing Company

Estimates/Events	3/12/2019	3/10/2020
Intercept	0.000	-0.001
Slope (beta)	0.752	1.005
Standard Error	0.011	0.011
R squared	0.338	0.444
CAR(0,1)	-0.003	0.002
CAR(-1,1)	-0.015	-0.045
CAR(-2,2)	-0.001	-0.136
CAR(-3,3)	0.006	-0.119
CAR(-5,5)	0.019	-0.114
AR(0)	-0.004	0.031

Table 6.3: Event Study Estimations for Wells Fargo & Company

Estimates/Events	8/5/2019	9/4/2019
Intercept	0.001	0.000
Slope (beta)	0.574	0.639
Standard Error	0.009	0.009
R squared	0.322	0.342
CAR(0,1)	-0.011	-0.009
CAR(-1,1)	-0.008	-0.002
CAR(-2,2)	-0.005	-0.008
CAR(-3,3)	-0.018	0.009
CAR(-5,5)	-0.048	0.004
AR(0)	-0.016	0.004

Table 6.4: Event Study Estimations for Walmart Inc.

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