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AN ANALYSIS OF THE US PRESIDENT TRUMP’S IMPACT ON THE FINANCIAL MARKETS THROUGH TWITTER POSTS

Ljubljana, November 2019 LAURA JARC

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LIST OF ABBREVIATIONS

n.d. no date
AAR average abnormal return
AAV average abnormal volume
APT arbitrage pricing theory
AR abnormal return
AV abnormal volume
BMP Boehmer, Musumeci, and Paulson
CAAR cumulative average abnormal return
CAAV cumulative average abnormal volume
CAPM capital asset pricing model
CO1 ticker for the Brent crude oil generic one month futures contracts
DJUSAU Dow Jones US Automobiles Index
EMH efficient market hypothesis
ES event study
EST Eastern Standard Time
EU European Union
NAFTA North American Free Trade Agreement
NASDAQ National Association for Securities Dealers Automated Quotations
NYSE New York Stock Exchange
OLS ordinary least squares
OPEC Organization of the Petroleum Exporting Countries
PCA principal component analysis
US United States of America
WTI West Texas Intermediate

INTRODUCTION

Donald J. Trump was elected on November 8, 2016, and therefore became the 45th President of the United States on January 20, 2017. When the results indicated that Trump would most likely win the election, volatility on markets increased. Near midnight on election night, futures for the benchmark S&P500 and Dow Jones Industrial Average indexes fell by more than 4%. A month after the election, it was evident that the financial sector had taken off under the assumption that a Republican administration would promote a more lenient regulatory environment. Biotech stocks also increased the day after the election. Trump's opponent Hillary Clinton during the campaign was often critical of pharmaceutical companies and their pricing policies. Her defeat suggested to the market that the regulatory environment for the pharmaceutical industry could also be more lenient than it was expected before the election. However, Trump's intentions to unravel Obamacare has hit healthcare stocks badly. The election also impacted foreign-exchange markets; Mexican peso fell to a record low (Kiersz, 2016).

As the President of the US, Trump has considerable influence on the economy, and his unpredictable Twitter behavior has become very famous. Twitter is an American online platform for news sharing and social networking where users can post messages known as "tweets," which are restricted to 280 characters. The platform allows users to "follow" people they are interested in. For example, Trump had 56.7 million followers at the end of 2018 and was one of the top 20 most-followed Twitter accounts in the world. He reaches even more people with his tweets due to "retweeting" (i.e., other users share his posts) and news coverage on his statements. On his Twitter account, Trump often criticizes or praises individual firms, and the evident sudden impact on stock prices of those companies was already covered by many news articles.

The Wall Street Journal prepared a study on stock prices of 12 companies Trump attacked on Twitter since February 12, 2016 (Figure 1). They questioned if his negative tweet could crush stocks and created a so-called Trump Target Index. The analysis included companies that traded on US exchanges. After tweets, stock prices often fell in intraday trade, but analysis showed that overall they have been resilient, and in the long-term Trump Target Index even outperformed the broader US stock market indices (Otani & Shifflett, 2017).

Furthermore, Bloomberg offers a webpage where they visualized the link between Trump's tweets and the Dow Jones Industrial Average. As Bloomberg describes, Trump often drew a direct connection between his administration's pro-growth policies and the increase in the market value of US companies.

Figure 1: Trump Target Index from February 12, 2016, until February 22, 2017

Source: Otani & Shifflett (2017).

The question that I will try to answer further is, how do Trump's tweets influence the stock value of a targeted company and its trading volume? Does he have the power to manipulate stock prices? To gauge the influence of Trump's posts on the individual stock prices of targeted companies, I used the event studies methodology.

The underlying assumption is a semi-strong form efficient capital market. There are nine basic steps to follow when conducting the analysis: define the event (i.e. tweet), specify the news sources and sample, recognize the event date, omit confounding events, form the event list, determine the estimation method, choose the estimation and event window, compute average abnormal returns (AAR) and cumulative average abnormal returns (CAAR), and perform statistical significance test (Event Study Metrics, n.d.).

The automotive industry was, aside from aerospace, drug manufacturers, and other firms, one of the most often attacked industries by Trump. Since it seems that this industry went through a turbulent period during Trump's presidency, I also questioned if Trump's Twitter attacks, together with his actions, helped increase the systematic risk for the automotive industry? In examining this question, I used PCA (principal component analysis), which shows the time evolution of the systematic risk in the industry.

In the following chapters, I will explain in detail the market efficiency and Twitter's influence, the methodology of event studies, the PCA, and the empirical findings from a set of chosen posts tweeted by Trump between November 8, 2016, and December 31, 2018.

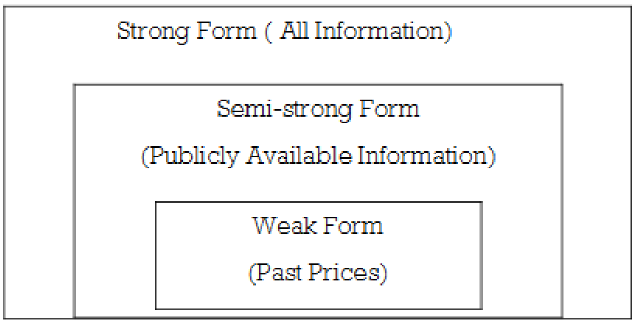
1 MARKET EFFICIENCY AND TWITTER'S INFLUENCE

An efficient market is when prices reflect all available and relevant information. As the definition of the EMH (efficient market hypothesis) states, for an efficient market to exist the following conditions must be met (Yalçın, 2010):

- there is active participation in the market with a large number of profit-maximizing rational investors;
- if some investors in the market are not rational, their irrational trades are offsetting one another, or their influence is eliminated by rational arbitrageurs;
- the information is free of costs and available at more or less the same time.

Fama differentiated three nested information sets that prices should reflect (Figure 2): past prices (weak form), publicly available information (semi-strong form), and all information (strong form, including private information) (Yalçın, 2010).

Figure 2: Three Forms of Market Efficiency



Source: Yalçın (2010).

The *weak form* suggests that all past market data is already reflected in the stock prices. The assertion is consistent with the random walk hypothesis, which states that the price changes through time are independent. Therefore, technical trading strategies cannot give consistent excess returns since the historical price movement cannot predict future price performance that is based on new information. However, one can beat the market and make superior profits by using insider trading or fundamental analysis (Yalçın, 2010).

For example, a trader might notice that a stock usually declines in value on Wednesdays and increases on Fridays. A trader could consider a strategy to make a profit by buying the stock at the beginning and selling it at the end of the week. If stock's price then actually turns down on Wednesday but does not shoot up on Friday, the market is weak-form efficient.

The semi-strong form claims that security prices reflect all publicly available information, that includes fundamental data. Therefore, with the usage of either the fundamental analysis or technical analysis, there is no superior profit. However, insider trading can still provide superior profits (Yalçın, 2010).

For example, a stock is trading at $20 one day before it is scheduled to report earnings. News report on that day claims that the company's business has suffered in the last period due to new regulations. When trading opens the next day, stock declines to $18. After the company officially reports positive results due to innovative products, the stock increases to $21. The material non-public information was news on innovative products that led to positive results. This is the only information that is considered useful for trading under the semi-strong form efficient market.

The strong form states that all publicly available information is reflected in market prices, including private information. Hence, even insider trading can not beat the market. The techniques could not work in the strong form efficient markets if they did not work in the weak form and the semi-strong form (Yalçın, 2010).

The efficient market creates a variety of events that indicate prices over-react to information. However, in an efficient market, under-reaction will be equally frequent as over-reaction. If inconsistencies split randomly between those two, they are consistent with market efficiency. Long-term return inconsistencies are sensitive to methodology, and when different statistical approaches are used to measure them or when exposed to different models for expected returns, they tend to vanish. Therefore, most long-term return inconsistencies can be reasonably ascribed to chance (Fama, 1998).

The market participants will occasionally fail, and some investors might be irrational. As a consequence, pricing inconsistencies or even foreseeable patterns in stock returns can become visible over time. Generally, the market cannot be completely efficient, or else there would be no incentive for participants to detect the information from which they could earn a profit (Malkiel, 2003).

The irrational investment decisions are called noise because market participants evaluate the securities on noise instead of using the information. Besides the risk that mispricing becomes more severe due to the noise traders, another imperfection against an arbitrage exists. Investors supply to arbitragers limited resources and increase or decrease the resources or even withdraw the investments causing the arbitrage position to cancel before it even profits (Yalçın, 2010).

A global financial crisis in the past several years has brought out the failure of the EMH, and there is a valid theoretical criticism of the hypothesis. Based on the EMH, it would be impossible for assets to be mispriced. If they were mispriced, there would be an instant arbitraging by informed players who would lead to a price correction. However, the fact is that some players are more rational than others (Subramanian, 2010).

Research also indicates that news can be unforeseeable. However, very early signals can be defined from online social media such as Twitter to forecast changes in various commercial and economic indicators. The public mood or sentiment can play as important role as news; all of them influencing stock prices (Bollen, Mao, & Zeng, 2011). Hence, market analysts are taking into account also Trump's tweets when making predictions.

Empirical work has, over the last several years, described a diversity of possibilities in which asset returns are forecasted with the use of publicly available information. Results show that returns appear to exhibit momentum or continuation in the short term and tendency towards reversals in the long term. Traditional asset-pricing models such as CAPM (capital asset pricing model) or APT (arbitrage pricing theory) have a difficulty explaining stock returns. As an alternative, many researchers are choosing the behavioral theories which deviate from the traditional assumptions of the unlimited computational capacity of the market participants and strict rationality. The vast number of deviations represent a challenge with this approach (Hong & Stein, 1999).

We know from the research in psychology that emotions, together with information, represent an essential role in individual decision-making. Besides news, sentiment or the public mood can also be the driver for stock market values. There has been remarkable progress in sentiment tracking techniques on how to extract measures of public mood from social media posts (i.e., blogs or Twitter feeds). Despite the fact that each tweet has a limited number of characters, the aggregate of the massive amount of tweets can provide a representation of sentiment or public mood (Bollen, Mao, & Zeng, 2011).

There are different kinds of stock traders, each of them with a somehow different style and field of focus. One of the many obstacles that any trader faces is the tendency of the human mind to make sudden decisions based on emotions or fear and not facts. The market has been paying attention to Trump's tweets, and while the expression "Trump Trade" (i.e., a trade based on Trump's post) has become an addition to Wall Street jargon, the data gathered suggests that it can be risky relying solely on tweets to make decisions about trades (StocksToTrade.com, 2017).

For example, the fake tweet that was posted from the hacked Twitter account of Associated Press diminished 140 points of the Dow Jones Industrial Average and temporary shook commodities and futures markets in 2013. Traders and hedge funds in recent years created algorithms that know how to read news and sentiment, and can also perform automated trades, which has taken Twitter-based trading even further (Stafford, 2015).

Trump's tweets can, therefore, be received as news on markets that will reflect in stock prices, commodity prices, and other market indices. His tweets might also create some noise (i.e., information that confuses or misrepresents genuine underlying trends) on markets since they are not necessarily verified information, sometimes they can represent only the criticism or a sentiment. These temporary shocks can hide the real value of securities and may result in mispricing.

Trump's Twitter behavior has led people to a widespread debate about whether he is doing it on purpose, so he could buy low and sell high. However, no evidence suggests that Trump is trying to manipulate the markets for his personal gain.

2 EVENT STUDIES AND PCA METHODOLOGY

Event studies can give guidance about how a stock is expected to react to the given event. I used the event studies methodology in order to establish if Trump's posts influence the individual stock prices of targeted companies.

The finance theory indicates that all available information and expectations about the prospects are reflected in the stock prices of firms. Three most critical underlying assumptions of the event study methodology are (Eventstudytools, n.d.):

- the influence of the event is accurately reflected in stock returns over the event window which means that capital markets are efficient;
- the event is not anticipated;
- there are no other events during the event window that could be responsible for the stock price change.

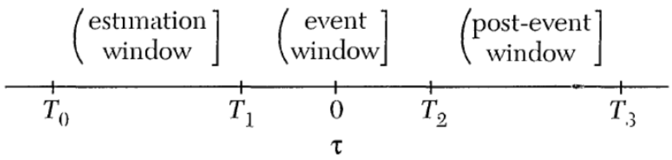
The event studies have been put to practical use for many economy-wide and company-specific events. Examples include earnings announcements, mergers and acquisitions, and issues of new debt or equity. The focus in the majority of applications is the event's impact on the price of common equity. Firstly, we need to determine the events and define the period for examination of stock prices. The estimation window needs to be defined. Generally, the estimation period does not include the event period in order to prevent the event from influencing the parameter estimates (MacKinlay, 1997).

It is unlikely that the estimation window determination will significantly influence the results. There is not expected a significant difference in the relationship between stock returns and market returns if an estimation window length is two months or one year before the event. The assumption is that the firm did not experience any major change. However, there is a trade-off between windows with a larger data sample and shorter estimation windows, which are more likely to be affected by the event (Krivin, Patton, Rose, & Tabak, 2003).

The length of the estimation and event windows is an individual choice. The challenge is to find the trade-off between potential parameter shifts and improved estimation accuracy. Longer estimation windows will have higher accuracy, but they also have the risk of confounding events, which can give biased estimators (Eventstudytools, n.d.). The event window covers the days around the event (i.e., tweet) when there is an expected influence on the stock price or volume due to new information.

Holler's empirical analysis on 400 event studies discovered that lengths of the estimation window are moving on an interval between 30 and 750 days. Sensitivity studies suggest that when the length exceeds 100 days, the results are not sensitive to different estimation window lengths anymore. Event windows usually move on an interval between 1 and 11 days and are symmetrical around the event day (Holler, 2012).

Figure 3: Event Studies Timeline



Source: MacKinlay (1997).

Returns in event time are indexed using τ, where $\tau = 0$ represents the event date. We define the timeline, as shown in Figure 3 for an event study as follows (MacKinlay, 1997):

- T_0 to T_1 is the estimation period where we will use OLS regression, which explains the relationship between an independent and a dependent variable, to get the coefficients for the calculation of the abnormal returns (the estimation window used will have the length of 250 trading days, $L_1 = T_1 - T_0 + 1 = 250$). I selected the estimation window with 250 trading days in order to achieve reasonable accuracy. There is only a slighter possibility of overlapping events.
- T_1 to T_2 is the event period for which we will calculate abnormal returns (the event window will have the length of 11 trading days, $L_2 = T_2 - T_1 = 11$). The event window goes around the event date from -5 to +5 days (i.e., one trading week) in order to see and analyze the movements in abnormal returns, although, I do not expect the impact of a tweet to be longer than one trading day.
- T_2 to T_3 is the post-event period (usually not considered, used only to investigate long-term performance following the event).

We have to decide which index will measure "normal" movements on the market. Usually, we choose the index that has, in the estimation window, the strongest explanatory power. However, it may be more reasonable to stick to a broader market index in a situation when we have analyzed a large number of stocks, instead of testing for each case more proper indices (Krivin, Patton, Rose, & Tabak, 2003).

The abnormal returns can be calculated with the parameter estimation for the normal performance model. The abnormal returns describe the unusual profits generated by given securities. They are also called alpha or excess returns. For abnormal returns, we have to design the testing framework. Essential considerations are determining the techniques for aggregating the individual company abnormal returns and defining the null hypothesis (MacKinlay, 1997). Based on this, we can investigate the importance of a particular event by examining its impact on the firm's stock price. Finance literature discusses different expected return models.

2.1 Expected Return Models

Statistical models do not depend on any economic arguments; they are rather based on statistical assumptions that follow the behavior of asset returns. An assumption that asset returns are jointly multivariate normal, independently, and identically distributed through time is imposed. That is enough for models to be correctly specified and usually does not lead to issues because it is empirically reasonable. It suggests that using normal return models tends to be robust to deviations (MacKinlay, 1997).

Below I will briefly describe different available approaches. I decided to use a market model, which is easy to implement; it does not impose any further restrictions and is also a common and basic approach that gives good results.

2.1.1 Constant Mean Return Model

Suppose that expected asset returns for the individual firm differ; however, they are constant over time. Let μ_i be the mean return for asset i, $R_{i\tau}$ is the period τ return on asset i and $\varepsilon_{i\tau}$ is the period τ disturbance term. Constant mean return model is:

$$R_{i\tau} = \mu_i + \varepsilon_{i\tau}, \tag{1}$$

where $E[\varepsilon_{i\tau}] = 0$ and $VAR[\varepsilon_{i\tau}] = \sigma^2_{\varepsilon_i}$. Constant mean return model is the most basic model, although it often gives results that are close to the more advanced and complicated models (MacKinlay, 1997).

2.1.2 Market Model

The market model is established on the company's stock correlation with the actual returns of a reference market. The relationship between the stock and the market needs to remain stable so that α and β coefficients, which were established during the estimation window with regression analysis, can be reliably used to predict during the event window the expected returns (Eventstudytools, n.d.).

Let $R_{m\tau}$ and $R_{i\tau}$ be the market portfolio and the period τ returns on asset i. α_i, β_i, and $\sigma^2_{\varepsilon_i}$ are the respective parameters. For any asset i, the market model is:

$$R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{i\tau}, \tag{2}$$

where $E[\varepsilon_{i\tau}] = 0$ and $VAR[\varepsilon_{i\tau}] = \sigma^2_{\varepsilon_i}$. The market model shows a development from the constant mean return model due to an extraction of the related portion of the return to the variation in the market's return. Therefore, the variance of the abnormal return is reduced. A benefit when using the market model depends on R^2 from regression. Higher R^2 suggests greater variance reduction in the abnormal return, therefore a better model (MacKinlay, 1997).

To assess the influence of an event, we need a measurement of the abnormal returns, which are calculated as the actual stock return ($R_{i\tau}$) minus the normal return (Eventstudytools, n.d.). For firm i and time period τ the abnormal return is:

$$AR_{i\tau} = R_{i\tau} - (\alpha_i + \beta_i R_{m\tau}). \tag{3}$$

Market-adjusted Model

The choice of models is often dependent on data availability. The market-adjusted model can be used in cases where there is limited data, and it is not feasible to have a pre-event estimation window. It can be considered as a restricted market model with α_i as zero and β_i as one. The estimation period is not required since the model coefficients are already determined. It is recommended to use a restricted model only if necessary, and even then, we need to think about the potential biases resulting from the restrictions (MacKinlay, 1997). We calculate the abnormal return as:

$$AR_{i\tau} = R_{i\tau} - R_{m\tau}. \tag{4}$$

Market Model with Scholes-Williams Beta Estimation

Stock trading (e.g., NYSE) usually does not occur synchronously. The trading frequency can vary from hour-to-hour and from day-to-day. OLS estimates become biased and inconsistent when the return on the market index and the return on the asset are measured over a different trading interval (Brown & Warner, 1985).

For non-synchronous trading, we can select the market model with Scholes-Williams beta estimation (instead of OLS). The β is defined as:

$$\beta_i^{SW} = \frac{\beta_i^- + \beta_i + \beta_i^+}{1 + 2\rho_M}, \tag{5}$$

where is β_i^- the regression coefficient of $R_{i\tau}$ on $R_{m,\tau-1}$, β_i^+ the regression coefficient of $R_{i\tau}$ on $R_{m,\tau+1}$ and ρ_M is the first-order autocorrelation of R_m (Eventstudytools, n.d.). The intercept α_i^{SW} is estimated through the sample mean:

$$\alpha_i^{SW} = \bar{R}_{i,EST} - \beta_i^{SW} \bar{R}_{m,EST}, \tag{6}$$

where $\bar{R}_{i,EST}$ is the mean of returns of the i-th observation in the estimation window and $\bar{R}_{m,EST}$ the mean of returns on the reference market in the estimation window (Eventstudytools, n.d.).

The consistent estimator of beta is based on the assumption of the uncorrelated returns through time. Empirical evidence shows that of thinly traded assets, adjusted beta estimates are larger than the unadjusted estimates. The adjustments are usually small for actively traded securities (MacKinlay, 1997). Considered companies in the sample are listed either on NYSE or NASDAQ, and their stocks are actively traded. Hence, I did not foresee the significant advantages of using a more complicated market model with Scholes-Williams beta estimation.

2.1.3 Other Statistical and Economic Models

Many other statistical models were developed for normal return modeling (i.e., factor models). Explaining a larger part of the variation in the normal return can lead to the benefits of reducing the variance in the abnormal return. The market model is a case of a one-factor model. In addition to the market indices, multifactor models also include industry indices. Due to the small marginal explanatory power of additional factors, the gains from using a multifactor model are limited (MacKinlay, 1997).

Economic models are not based only on statistical assumptions and rely on assumptions regarding investors' behavior. The opportunity to have more precise measures of the normal return can lead to a potential advantage of economic models. However, economic models can apply restrictions on statistical models to create more constrained normal return models. Two conventional economic models that provide restrictions are the CAPM and APT. With CAPM, there were discovered deviations, indicating that the validity of the imposed restrictions is questionable. The popularity of the CAPM has, therefore, almost disappeared because of the mentioned sensitivity on restrictions. The APT is also rarely used because additional factors add quite little explanatory power. Hence, a better choice is a simple market model (MacKinlay, 1997).

2.2 Model Selection and Data Aggregation

Holler's empirical analysis confirmed that the market model is the most common method used. Based on a sample of 400 event studies, 79.1% of them used the market model, 13.3% chose the market-adjusted model, 3.6% multifactor models, 3.3% the constant mean return model, and 0.7% used the CAPM model (Holler, 2012). I decided to use a market model since it gives good results, it is easy to implement, and it does not impose any further restrictions.

For the i^{th} company, the OLS estimators in the estimation window of the market model parameters are (MacKinlay, 1997):

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1}(R_{i\tau}-\hat{\mu}_i)(R_{m\tau}-\hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1}(R_{m\tau}-\hat{\mu}_m)^2}, \tag{7}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\hat{\mu}_m, \tag{8}$$

$$\sigma_{\varepsilon_i}^2 = \frac{1}{L_1-2}\sum_{\tau=T_0+1}^{T_1}\left(R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}\right)^2, \tag{9}$$

where $\hat{\mu}_i = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{i\tau}$ and $\hat{\mu}_m = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{m\tau}$. $R_{i\tau}$ and $R_{m\tau}$ are the returns in event period τ for asset i and the market.

Since we have chosen our expected return model, defined the length of our event and estimation windows, the next step is to choose the reference index and calculate abnormal returns. As already described, choosing the market model for measuring the normal returns, the abnormal returns are (MacKinlay, 1997):

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}. \tag{10}$$

The abnormal returns with conditional variance $\sigma^2(AR_{i\tau})$ and a zero conditional mean are jointly normally distributed under the null hypothesis where (MacKinlay, 1997):

$$\sigma^2(AR_{i\tau}) = \sigma_{\varepsilon_i}^2 + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau}-\hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right]. \tag{11}$$

There are two components of conditional variance. First one is the disturbance variance $\sigma_{\varepsilon_i}^2$, and the second one is an additional variance due to the sampling error in α_i and β_i. The sampling error can, despite the independence of true disturbances, also lead to the serial correlation of the abnormal returns. However, the second term will go to zero when the length of the estimation window L_1 becomes large enough. Hence, the sampling error disappears, and the variance of the abnormal returns becomes equal to $\sigma_{\varepsilon_i}^2$. Abnormal returns are independent through time (MacKinlay, 1997). Therefore, I chose the estimation window with 250 trading days.

In order to get cumulative abnormal returns or average abnormal returns, abnormal returns are aggregated across time or cross-sectional. Tests with just one event observation are usually not useful (i.e., test with one tweet will not be enough to conclude that Trump can affect markets with his posts). The usual stock market response patterns can be seen if we perform analysis for multiple events of the same event type (Eventstudytools, n.d.). Average abnormal returns are defined as:

$$AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}\ . \tag{12}$$

The assumption is that in the event windows of the included assets, we do not have any overlap (i.e., clustering). To avoid overlapping, I mainly chose only one tweet per company. The abnormal returns will be independent across assets due to the absence of clustering and the maintained distributional assumptions. For large L_1, the variance becomes $var(AAR_\tau) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_{\varepsilon_i}^2$ (MacKinlay, 1997).

The total influence of an event through a period of time ($T_1 < \tau_1 \leq \tau_2 \leq T_2$) is measured with a cumulative abnormal return. I will apply an 11-day event window that starts at $\tau_1 = -5$ and ends at $\tau_2 = +5$:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}. \tag{13}$$

As L_1 increases the variance for CAR_i becomes $\sigma_i^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1)\sigma_{\varepsilon_i}^2$. Nevertheless, the variance should be adjusted for the impact of the estimation error for small values of L_1 (MacKinlay, 1997).

Aggregating the abnormal returns across time and companies results in the cumulative average abnormal returns. When we have multiple event types of observations (e.g., tweets), we can additionally calculate the cumulative average abnormal returns (MacKinlay, 1997):

$$CAAR(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1, \tau_2), \tag{14}$$

$$var\big(CAAR(\tau_1, \tau_2)\big) = \sum_{\tau=\tau_1}^{\tau_2} var(AAR_\tau) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(\tau_1, \tau_2). \tag{15}$$

To set the covariance terms to zero, we use the assumption that the event windows do not overlap. It is essential to understand that the covariance between the abnormal returns will not be zero when the even windows overlap. Therefore, the distributional results introduced for the aggregated abnormal returns are not applicable any more (MacKinlay, 1997).

2.3 Significance Tests

In order to establish if the abnormal returns found are statistically significant and, therefore, valid, we use the significance tests. This assessment is performed by hypothesis testing. Null hypothesis (i.e., H_0) suggests that within the event window, there are no abnormal returns. Contrary, the alternative hypothesis (i.e., H_1) indicates the presence of abnormal returns in the event window. Technically, the testing framework is written as (Müller, n.d.):

$$H_0\colon \mu = 0,$$

$$H_1\colon \mu \neq 0.$$

Generally, significance tests are parametric or nonparametric. Parametric tests have an assumption that the company's abnormal returns are normally distributed, but such assumptions do not hold for nonparametric tests (Müller, n.d.).

A decision on test statistics should be based on the statistical issues of the data that has been analyzed. When determining event and estimation windows, we can run into issues with (Müller, n.d.):

- cross-sectional correlation of abnormal returns when we focus on events that happened on the same day for multiple firms and
- distortions from event-induced volatility changes that become an issue when there are clustered events.

Both issues can introduce in the standard deviation a downward bias and thus overstate the t-statistic, which leads to the over-rejection of the null hypothesis.

Generally, parametric tests can deal with data that is not normal, and we have to be careful with nonparametric tests because they can have strict assumptions. The decision usually depends on whether the median or mean more accurately represent the center of the distribution (Minitab, 2015):

- decide for a parametric test because it is more powerful when a mean represents the center and the sample size is large enough;
- when a median, decide for the nonparametric test even if there is a large sample size.

2.3.1 Parametric Tests

Parametric tests have a few underlying assumptions regarding statistical distribution in the data. For the result of a parametric test to be reliable, several conditions must hold. Parametric test statistics are based on the classical t-test and have the advantage of higher statistical power since they are more likely to lead to a rejection of H_0. A few reasons when we should use parametric tests (Minitab, 2015):

- they can perform well when the distribution is skewed and non-normal under some sample size requirements (e.g., greater than 20 for 1-sample t-test, each group greater than 15 for 2-sample t-test);
- they can perform well when each group has a different spread (nonparametric tests have an assumption that the data must have the same spread in all groups and when this does not hold they might not provide valid results);
- and as already mentioned, they generally have higher statistical power than nonparametric tests (i.e., more likely to detect a significant effect).

T-Test and Cross-Sectional Test

The t-test's strength is its simplicity but can have potential issues with volatility changes and cross-sectional correlation. The null hypothesis and respective t-test are written as (Müller, n.d.):

$$H_0: AR_{i\tau} = 0,$$

$$t_{AR_{i\tau}} = \frac{AR_{i\tau}}{sd_{AR_i}}, \tag{16}$$

where sd_{AR_i} is the standard deviation in the estimation window of the abnormal returns. It can be written as (Müller, n.d.):

$$sd^2_{AR_i} = \frac{1}{M_i-2}\sum_{\tau=T_0}^{T_1}(AR_{i\tau})^2. \tag{17}$$

M_i corresponds to the number of matched returns. The standard deviation holds for the market model, and in the case of other models, some adjustments would be needed. To test on average abnormal returns, we can use a simple cross-sectional test with null hypothesis and t-test (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$t_{AAR_\tau} = \sqrt{N}\frac{AAR_\tau}{sd_{AAR_\tau}}, \tag{18}$$

where N is the sample size and sd_{AAR_τ} the standard deviation across firms at time t. It can be written as (Müller, n.d.):

$$sd^2_{AAR_\tau} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{i\tau} - AAR_\tau)^2\ . \tag{19}$$

However, the cross-sectional test is inclined to have a low power due to the event-induced volatility.

Patell or Standardized Residual Test

Its advantage is that the distribution of ARs in the event window does not matter, but it can be vulnerable to event-induced volatility and cross-sectional correlation. Patell test is a common test statistic in event studies where we standardize ARs with the forecast-error corrected standard deviation (Müller, n.d.):

$$SAR_{i\tau} = \frac{AR_{i\tau}}{sd_{AR_{i\tau}}}. \tag{20}$$

Patell adjusts the standard deviation with the forecast-error because the event window ARs are out-of-sample predictions (Müller, n.d.):

$$sd^2_{AR_{i\tau}} = sd^2_{AR_i}\left(1 + \frac{1}{M_i} + \frac{\left(R_{m\tau} - \overline{R}_m\right)^2}{\sum_{\tau=T_0}^{T_1}\left(R_{m\tau} - \overline{R}_m\right)^2}\right), \tag{21}$$

with $\overline{R}_m$ as the mean in the estimation window of the market returns. Under the null hypothesis, $SAR_{i\tau}$ has t-distribution with $M_i - 2$ degrees of freedom. The null hypothesis and test statistic for average abnormal returns are (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$z_{Patell,\tau} = \frac{ASAR_\tau}{sd_{ASAR_\tau}}, \tag{22}$$

where $ASAR_\tau = \sum_{i=1}^{N} SAR_{i\tau}$ with expectation zero and variance $sd^2_{ASAR_\tau} = \sum_{i=1}^{N} \frac{M_i - 2}{M_i - 4}$. Under some assumptions (e.g., cross-sectional independence), z_{Patell} has a standard normal distribution.

The adjusted Patell test is the modification of the Patell test to improve it for additional strength of immunity to the cross-sectional correlation of the abnormal returns. The average of the sample cross-correlation on the estimation window is defined as $\overline{r}$. The null hypothesis and test statistic for average abnormal returns are (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$z_{Patell,\tau} = z_{Patell,\tau}\sqrt{\frac{1}{1 + (N-1)\overline{r}}}. \tag{23}$$

The adjusted test statistic will get closer to the original test statistic if the correlation is zero.

Standardized Cross-Sectional or BMP Test

Its advantages are that the distribution of ARs across the event window does not matter, and it takes into consideration the serial correlation and event-induced volatility. On the other hand, it also has a weakness, which is vulnerability to cross-sectional correlation. To the variance induced by the event, BMP test is robust. The null hypothesis and test statistic for average abnormal returns are (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$z_{BMP,\tau} = \frac{ASAR_\tau}{\sqrt{N} sd_{ASAR_\tau}}, \tag{24}$$

where $ASAR_\tau = \sum_{i=1}^{N} SAR_{i\tau}$ and variance $sd^2_{ASAR_\tau} = \frac{1}{N-1}\sum_{i=1}^{N}\left(SAR_{i\tau} - \frac{1}{N}\sum_{l=1}^{N} SAR_{l\tau}\right)^2$.

The adjusted BMP test is the modification of the BMP test to improve it for additional strength with consideration of cross-sectional correlation. The average of the sample cross-correlation on the estimation window is defined as $\bar{r}$. The null hypothesis and test statistic for average abnormal returns are (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$z_{BMP,\tau} = z_{BMP,\tau}\sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}}. \tag{25}$$

The adjusted test statistic will get closer to the original test statistic if the correlation is zero.

2.3.2 Nonparametric Tests

Nonparametric tests do not depend on distribution and can be used in cases when underlying assumptions regarding statistical distribution are not met. These types of tests are more robust and are valid in a broader range of situations. A few reasons when we should use nonparametric tests (Minitab, 2015):

- median better represents the center of the distribution (changes far out in the distribution's tail are affecting the mean);
- a small sample size (we cannot be confident about data distribution if we do not meet the sample size requirements for the parametric tests);
- and ranked data, ordinal data, or outliers that we cannot remove.

In the case of a small sample, there will be insufficient power of the distribution tests in order to provide meaningful results. Hence, when we use nonparametric tests on small sample size, our chances of observing a significant effect are very small (Minitab, 2015).

The common nonparametric tests used are the sign test and the rank test. The sign test requires that the expected proportion of positive or negative abnormal returns under the null hypothesis is 0.5 since it is equally probable that the returns will be negative or positive and that AR or CAR are independent across assets. We have $H_0: p \leq 0.5$, and the alternative $H_1: p > 0.5$, where $p = pr[CAR_i \geq 0.0]$ in the case if the null hypothesis is that there is a positive abnormal return. We need the number of cases where the AR are positive N^+ and the total number of cases N, to assess the test statistic. We define t_{sign} as the test statistic (MacKinlay, 1997):

$$t_{sign} = \left[\frac{N^+}{N} - 0.5\right]\frac{\sqrt{N}}{0.5} \sim N(0,1). \tag{26}$$

The distributional result is asymptotic, and H_0 is rejected if $\theta_2 > \Phi^{-1}(\alpha)$ for a test size $1 - \alpha$. A disadvantage of the sign test is that it may be badly specified if the AR distribution is skewed. Corrado's rank test solves the mentioned issue since it does not require symmetry and transforms abnormal returns into ranks for the event and estimation window. If ranks are tied, the mid-rank is used. We define standardization of the ranks as (Müller, n.d.):

$$K_{i\tau} = \frac{rank(AR_{i\tau})}{1+M_i+L_i}, \tag{27}$$

where L_i refers to the number of return values in the event window, and M_i is the number of return values in the estimation window for a company i. The null hypothesis and test statistic for average abnormal returns are (Müller, n.d.):

$$H_0: AAR_\tau = 0,$$

$$t_{rank,\tau} = \frac{\overline{K}_\tau - 0.5}{sd_{\overline{K}}}, \tag{28}$$

where $\overline{K}_\tau = \frac{1}{N_\tau}\sum_{i=1}^{N_\tau} K_{i\tau}$, $sd_{\overline{K}}^2 = \frac{1}{L_1+L_2}\sum_{\tau=T_0}^{T_2} \frac{N_\tau}{N}\left(\overline{K}_\tau - 0.5\right)^2$, and N_τ is the number of returns across companies.

Nonparametric tests are usually not used individually but together with the parametric counterparts. With their inclusion, we provide the check of robustness in conclusions that are based on parametric tests (MacKinlay, 1997).

2.4 Abnormal Trading Volume

Trading volume represents an important role in financial markets since it allows investors to share financial risks, incorporates the price discovery process, and provides that corporations can raise needed funds for investments (Chae, 2005).

Along with return event studies, we can also investigate, if trading volumes of stocks display statistically significant inconsistencies. The main difference of abnormal volume from abnormal return event study is that the log-transformed relative volume per company is used rather than returns (Eventstudytools, n.d.):

$$V_{i\tau} = \log\left(\frac{n_{i\tau}+0.000255}{S_{i\tau}} \times 100\right), \tag{29}$$

where $n_{i\tau}$ is the number of stocks traded for a company i and $S_{i\tau}$ is the outstanding share. It is recommended by many authors to use the log-transformed value instead of formula $V_{i\tau} = \frac{n_{i\tau}}{S_{i\tau}} \times 100$. To avoid the log-transformation on zero values, a small constant 0.000255 is added (Eventstudytools, n.d.).

The market model for abnormal trading volume is (Campbell & Wasley, 1996):

$$\nu_{i\tau} = V_{i\tau} - (\alpha_i + \beta_i V_{m\tau}), \tag{30}$$

where α_i and β_i are obtained from OLS estimation.

Market volume measure for a given day τ is measured as (Campbell & Wasley, 1996):

$$V_{m\tau} = \frac{1}{N} \sum_{i=1}^{N} V_{i\tau}, \tag{31}$$

where N is the number of assets in the market index.

2.5 Possible Biases and Issues

When conducting an event study, some other questions or issues arise (MacKinlay, 1997):

- *Sampling Interval Selection*: Data can be available at different intervals, the most commonly used are daily and monthly stock returns. The question here would be what the gains of using shorter intervals are? MacKinlay's research showed that when using a monthly interval rather than daily, there was a severe decrease in power. We could also decide to analyze even shorter intervals (e.g., hourly stock returns), but the benefits from that are unclear as some complications are introduced.
- *Defining Event Date*: So far, we assumed that the event date could be identified with certainty. When we are not sure about exact timing when the market was informed, we can widen the event window to two days. In our case, it was a challenge to select only the posts that are holding some new information that was not already communicated to the market.
- *Robustness*: The assumption that returns are jointly normal and temporally independently and identically distributed is the basis for statistical analysis. For the exact finite sample results to hold, the normality assumption is essential.
- *Non-synchronous Trading*: This issue comes from a situation when prices are taken at time intervals of irregular lengths. For example, with daily stock returns, we usually look at the closing price, a price at which the last transaction occurred during the trading day. However, closing prices usually do not occur each day at the same time. We are incorrectly assuming that they are equally spaced at 24-hour intervals by calling them daily prices. This induces biases in the moments and co-moments of returns.

When reading through Trump's tweets, it can be noted that he is often tweeting about the same company multiple times and creating "events" in short time intervals. Frequent tweeting about the same companies can cause an issue because the estimation window of an event might overlap with the estimation window of a previous event or with the event itself, which would affect the results. In order to address this problem, the earliest event is used, ignoring the subsequent ones.

The study will be much simpler if a set of observations for each company is matched to a single event date. Therefore, I will almost always choose only one tweet per company, since the testing period from November 8, 2016, until December 31, 2018, is not so long. We can also examine more than one event date for each company, where it is necessary to create a duplicate set of observations for each combination.

2.6 Principal Component Analysis

The automotive industry was besides aerospace, drug manufacturers, and some other firms, one of the most often attacked industries by Trump. Since it seems that this industry went through a turbulent period during Trump's presidency, I also questioned if Trump's Twitter attacks, together with his actions, helped increase the systematic risk for the automotive industry. To examine that, I used principal component analysis.

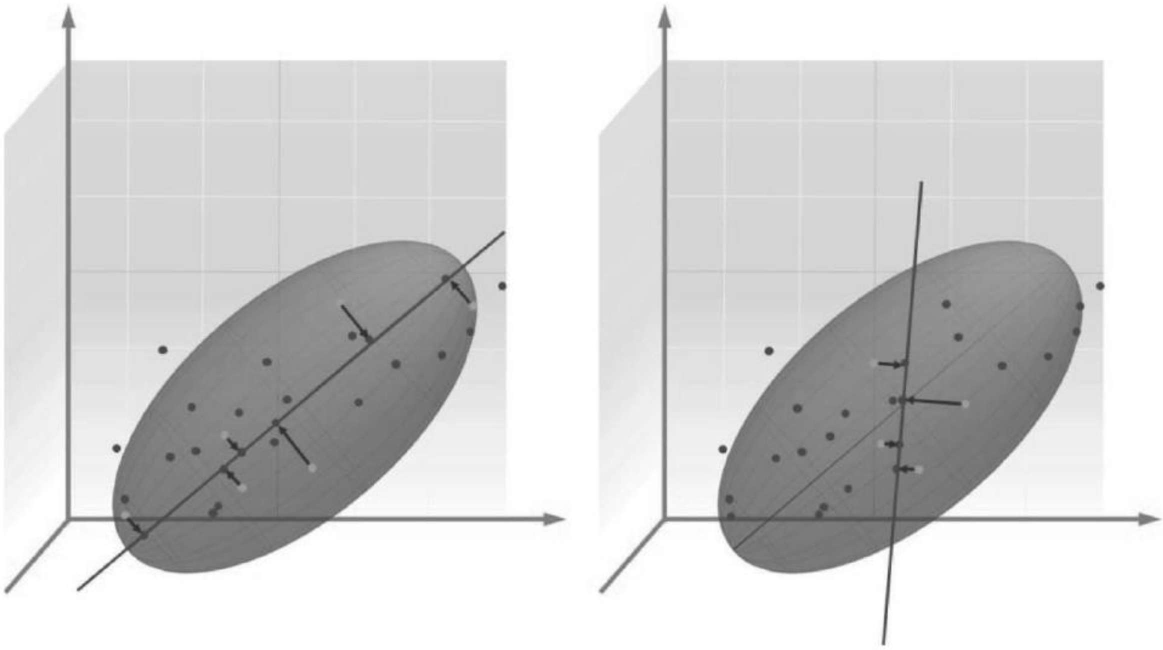
The failure of the US government to provide adequate oversight and regulation of the financial markets and their excessive risk-taking lead the economy in 2008 to the next financial crisis. Hence, the regulators and investors became more interested in developing tools to monitor systematic risk accurately so that they could mitigate it sooner. One of the measures for the systematic risk that was introduced can be the principal component (Kritzman, Li, Page, & Rigobon, 2010).

Systemic risk can be described as the risk that is associated with the financial system or any set of circumstances that can potentially initiate a financial crisis. The increase in the systemic risk indicates that the amount of idiosyncratic risk (i.e., diversifiable) decreases, which leaves the investor less prepared for negative shocks in the financial markets (Yang, Rea, & Rea, 2015). Hence, the increasing systematic risk that cannot be diversified away can indicate a downturn in the market that awaits.

Visualization of data when there are many variables is one of the struggles in multivariate statistics. However, groups of variables often move together. One of the explanations is that more than one variable might be measuring the same driving principle. Replacing a group of variables with a single new variable can simplify the problem, and the PCA is a method to do that. There is no unnecessary information, since all principal components are orthogonal to each other (MathWorks, n.d.).

The first eigenvector has the greatest variance of the projected observations (Figure 4). The eigenvalues are the constants that increase or decrease the eigenvectors along their span when they are transformed linearly. We can imagine eigenvectors and eigenvalues as the summary of a large matrix. The second eigenvector yields the second highest variance of projected observations and must be orthogonal to the first eigenvector. Similarly, the third eigenvector yields the third greatest variance and is orthogonal to the first two. In the case of a three-dimensional scatter plots for three assets, mentioned three vectors together explain the total variance of the assets (Kritzman, Li, Page, & Rigobon, 2010).

Figure 4: Projection of Observations onto Vectors (Three-Dimensional)



Source: Kritzman, Li, Page, & Rigobon (2010).

The full set of principal components is as big as the original set of variables. The sum of the variances of the first few principal components often exceeds 80% of the total variance of the original data. Hence, the researchers often develop a deeper understanding of what drives the original data when they examine plots of a few new variables (MathWorks, n.d.).

The amount of variation that is explained by individual principal component is determined by (Yang, Rea, & Rea, 2017):

$$Variation\ Explained\ by\ Component\ j = \frac{\lambda_j}{\sum_{i=1}^{n} \lambda_i} \times 100, \tag{32}$$

where λ_i is the eigenvalue of component i. A linear combination of all variables is represented by the eigenvector of each principal component and can be written as (Yang, Rea, & Rea, 2017):

$$\alpha_n' x = \sum_{i=1}^{n} \alpha_{ni} x_i, \tag{33}$$

where $\alpha_n' x$ is the eigenvector of component n, and α_{ni} is the coefficient of variable i in component n. For each principal component n (Yang, Rea, & Rea, 2017):

$$\sum_{i=1}^{n} \alpha_{ni}^2 = 1. \tag{34}$$

If variables x_1 and x_2 are two highly correlated variables in component n, they will have large coefficients, and the other variables will have coefficients close to zero (Yang, Rea, & Rea, 2017):

$$\alpha_{n1}^2 + \alpha_{n2}^2 + \sum_{i=3}^{n} \alpha_{ni}^2 = 1, \tag{35}$$

where $\sum_{i=3}^{n} \alpha_{ni}^2 \approx 0$, so that $\alpha_{n1}^2 + \alpha_{n2}^2 \approx 1$. Therefore, the closer α_{n1} and α_{n2} are in magnitude, the more correlated are variables x_1 and x_2.

Hence, PCA is a statistical method that extracts an ordered set of uncorrelated sources of variation. Financial markets usually integrate a high degree of multicollinearity, which makes the PCA an attractive method to apply. We can decompose the correlation matrix into three parts, and the principal components have the following meaning (Yang, Rea, & Rea, 2015):

1. The first principal component (PC_1) has the largest eigenvalue and is interpreted as a market-wide effect that influences all stocks; hence, it is also known as the systematic risk.
2. Principal components that follow the market component are interpreted as the synchronized fluctuations that are associated with specific groups of stocks.
3. The remaining principal components indicate randomness in the price fluctuations, which is also known as noise. They do not contain any useful information and should be eliminated from further research.

When the correlation between assets increases, the systemic risk is higher because shocks can spread more broadly and quickly; therefore, monitoring the time evolution of correlation is very important. The PCA can be used on either a covariance matrix or a correlation matrix (Yang, Rea, & Rea, 2015).

3 EMPIRICAL FINDINGS

In the following subsections, I review Trump’s Twitter activity, describe data collection and selected tweets, review Trump’s influence on currency exchange and commodity markets, apply the event study methodology on selected groups of tweets, and conduct a PCA on the US automotive industry.

3.1 Trump’s Twitter Activity

Reading Trump’s tweets, the first thing that can be noticed is how simple his language is. Simple words are effective. Trump’s choice of adjectives is also effortless; by far, the most common one in his vocabulary is “great.” Figure 5 represents the words that Trump most often tweeted from November 8, 2016, until December 31, 2018.

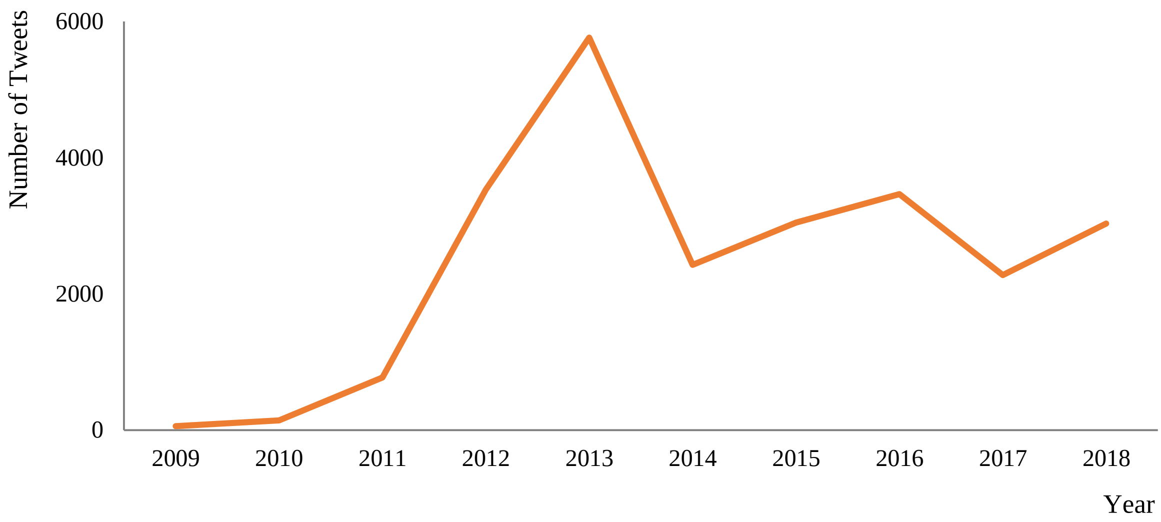
Figure 5: Trump's Tweets Represented in a "Word Cloud"

Source: WordClouds.com (n.d.).

The first tweet posted by Trump was in May 2009, promoting his appearance on The Late Show. That was more than ten years ago. According to his Twitter profile, he has posted approximately 40,100 tweets from May 2009 through the end of 2018. Looking through the whole base of Trump's tweets, we can see how much he has used the service over time. Trump's Twitter use peaked in 2013 with posts about Obama and declined since he became president in 2017. Since taking office, he has been tweeting less, but each tweet gets far more attention than before due to his more extensive follower base and the important role he has as the president. We should also consider that in late 2017, Twitter increased the maximum number of characters per tweet from 140 to 280. Trump's frequency of tweeting is represented in Figure 6.

According to the "Trump Twitter Archive" website, his hot topic since becoming the president has been "fake news," followed by tweets that mention The Washington Post, CNN, NBC, and The New York Times. The main focus seems to be his obsession with media coverage. Of all of his tweets, only the most dramatic are seen by the majority of Americans. Not many use Twitter, but they mainly hear about his tweets when they are later reported in the media.

Figure 6: Trump's Number of Tweets per Year since 2009



Source: Own work.

The total number of people that follow Trump's Twitter profile has increased substantially since he became president. The year-on-year increase in follower base shows more than a ten-time jump between the end of 2015 and 2018, the most significant increase coming from his election. This brought in a broader base of followers, and accordingly, the range in sentiment widened significantly with a lot more negative responses to his tweets. Nowadays, more than 17% of all users on Twitter follow him; at the end of 2018, he had a total of 56.7 million followers. The activity of Trump's followers has also grown in recent years, which has been driven mainly by the increase in the total number of followers. The total number of "favorites" on his tweets increased from 9.6 million in 2015 to more than 200 million in 2018. The average number of retweets per follower did not change significantly, but the average number of replies per follower tripled, which might be due to his broadened base of followers.

All of the above suggests that Trump's influence increased considerably in the past few years. Therefore, the reach of Trump's tweets in the last years is expected to have a more substantial potential impact on stock market returns. The period for analysis of tweets was chosen from November 8, 2016, through December 31, 2018, due to the aforementioned reasons.

3.1.1 Data Collection

I manually reviewed 6,338 tweets from Trump's personal account (@realDonaldTrump) and selected only a few of those that could be important for stock markets, commodity markets, or currency-exchange volatility. Famous "fake news" topics and mentions of news outlets such as The Washington Post, CNN, NBC, and The New York Times were excluded from this research.

Under the ES application, I analyzed each individual tweet's impact on traded volume and stock prices. Considered companies are listed either on NYSE or NASDAQ due to practical reasons since daily stock data is more accessible to gather. They also use the same time zone as tweets (EST), and most of Trump's posts targeted stocks on those two markets. Messages were chosen if they contained new information that was not already reported through other sources. This could be confirmed in cases where media coverage was taking his tweets as the source of information. However, despite the effort, results might be contaminated by other events besides Trump's tweets since the news about a company might become public via different sources simultaneously.

I retrieved daily stock and index data from Bloomberg Terminal. All data on targeted companies or the market proxy contain a closing price, trading volume, and outstanding shares on any day in the reviewed period. The market proxy that is the most appropriate for the overall analysis is S&P500, which is a market capitalization-weighted index comprised of the largest 500 US companies as measured by Standard and Poor's. For analysis performance, I used Matlab and aligned the data, so the dates on companies and markets would coincide.

Applying the PCA, I included in the sample as many stocks of vehicle manufacturers as possible even if they do not have the majority of their industry in the US. The criterion for selection was that the stock from the mentioned industry should be listed on the US markets. I retrieved daily stock and DJUSAU index data from Bloomberg Terminal and used Matlab for the analysis.

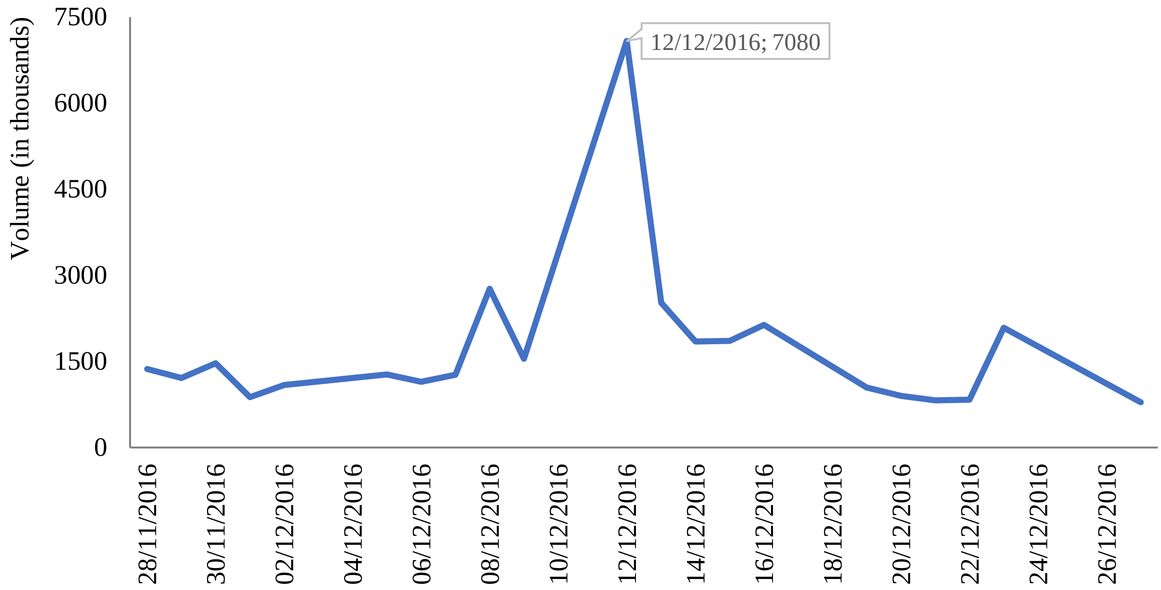
Data on currency exchange rates was retrieved via Thomson Reuters Eikon, and commodity price data was downloaded from Bloomberg Terminal.

3.1.2 Selected Tweets for the ES Application

One of the first Trump's tweets that affected the markets since his election was about Boeing on December 6, 2016, at 8:52 AM (EST), when he tweeted: *"Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!"* Stock market quickly took note, since Boeing is a major American corporation that gets money from the Pentagon and also employs a significant number of manufacturing workers in high-wage jobs. Boeing's stock price immediately dropped 1% which was based on a speculation, if the company will lose favor with the new administration, but the correction was temporary, Boeing's stock closing was unaffected. Therefore, Trump's post on Twitter only slightly affected the stock's volume.

A few days later, on December 12, 2016, at 8:26 AM (EST), Trump tweeted about Lockheed Martin's advanced fighter program: *"The F-35 program and cost are out of control. Billions of dollars can and will be saved on military (and other) purchases after January 20th."* The company is also highly owned by US investors. Lockheed Martin's stock price and shares of other companies that make components for the jet dropped significantly after Trump's post on Twitter. Lockheed Martin's stock price was down 2.5% toward the end of the trading day. In Figure 7, it is also shown how the stock's trading volume spiked on the mentioned day when the market received the information.

Figure 7: Trading Volume of Lockheed Martin's Stock around the Event Date



Source: Own work.

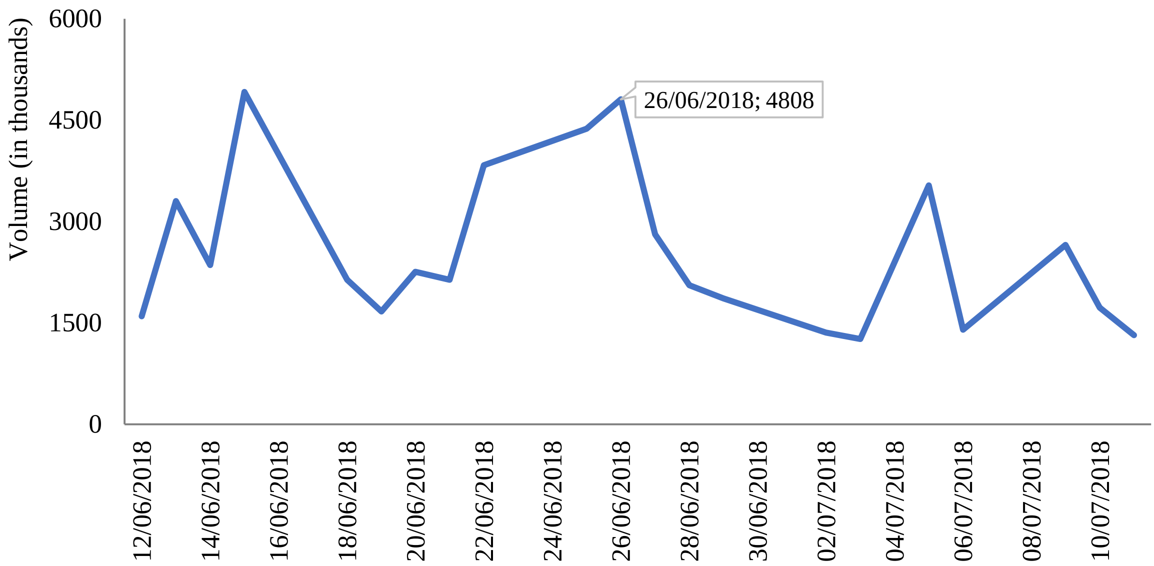
Later Trump added a few more posts about Boeing and Lockheed Martin, but his tweets did not receive as much attention as those two (i.e., media coverage or reaction in stock price/volume). However, it can be noted that markets are quite sensitive to his tweets about government contractors since they create speculation if any contracts might be voided or new ones signed, which would create significant additional revenue for involved companies.

Shortly after his election, Trump tweeted on November 17, 2016, that he received a call from Bill Ford, who said that Ford would be keeping the plant in Kentucky. The Washington Post later wrote that Ford never intended to move either of its plants in Kentucky to Mexico. On the contrary, the automaker committed to investing USD 700 million in the plant over the following years. Anyhow, the market did not react significantly to this post with a positive sentiment.

On January 5, 2017, at 1:14 PM (EST), Trump threatened Toyota: *"Toyota Motor said it will build a new plant in Baja, Mexico, to build Corolla cars for the US. NO WAY! Build a plant in the US or pay big border tax."* After the tweet, the company's US-listed stocks ticked about 0.7% lower, and its trading volume increased significantly on that day. Toyota responded in a statement to Reuters that the new Mexican plant will not cut its US employment.

Trump also targeted on June 25, 2018, the decision of Harley-Davidson to move production of some motorcycles overseas. The American motorcycle company announced on the same day earlier that it would shift the production of motorcycles for European consumers out of the US, hoping to avoid EU tariffs. Since Trump posted his tweet after trading hours, we can assume that a significant drop in Harley-Davidson's stock price on that day was due to their announcement. Trump's post affected the next day's trading statistics alongside their announcement's effect. The stock price was not affected by his post, but on the other hand, trading volume increased significantly (Figure 8).

Figure 8: Trading Volume of Harley-Davidson's Stock around the Event Date



Source: Own work.

Trump lambasted General Motors due to their decision to close a few plants in the US in a tweet on November 27, 2018, saying that he is very disappointed. One day earlier, the American automaker had announced that it would be cutting 15% of its North American workforce and halting production at several plants. General Motors' stock price slipped over 2% after the tweet.

In 2018, Trump tweeted about drug manufacturers such as Merck and Pfizer due to increased drug prices. His remarks did not have the desired influence since there was no evident reflection in the stock prices of those two pharmaceutical giants; it only temporarily increased their trading volumes.

Probably the most famous and numerous remarks were made against Amazon and its founder, Jeff Bezos. Trump targeted Amazon on August 16, 2017, at 6:12 AM (EST) with accusations: *"Amazon is doing great damage to tax-paying retailers. Towns, cities, and states throughout the US are being hurt - many jobs being lost!"* Amazon stock price dipped briefly by 1%. The frequency of Twitter attacks increased in 2018 when Trump aimed at the company, accusing it of paying too little in taxes and using the United States Postal Service as a "delivery boy." He also wrote a lot of criticism against The Washington Post and its owner, Jeff Bezos. On July 23, 2018, at 9:35 AM (EST), Trump tweeted: *"In my opinion, the Washington Post is nothing more than an expensive (the paper loses a fortune) lobbyist for Amazon. Is it used as protection against antitrust claims which many feel should be brought?"* In his criticisms, Trump hinted at future antitrust actions against the company. Shares of Amazon fell almost 2% in early trading before paring half the losses. The stock closed less than 1% down. Some of Trump's remarks about the company were partly true, but anyhow, they were mostly misleading. I used only two events on a larger time interval apart based on this confrontation, since I did not want that analysis weights too heavily on it.

Trump also took aim at the third-largest US bank on December 8, 2017, at 10:18 AM (EST), writing on Twitter: *"Fines and penalties against Wells Fargo Bank for their bad acts against their customers and others will not be dropped, as has incorrectly been reported, but will be pursued and, if anything, substantially increased. I will cut Regs but make penalties severe when caught cheating!"* One day earlier, Reuters reported that Wells Fargo was under investigation whether it should pay a considerable fine over the alleged mortgage lending abuse. Trump's post on potentially higher fines appeared to have only a moderate impact on the bank's stock price.

Among Trump's claims of bias against conservatives on the internet, he even accused Google on August 28, 2018, saying that they are controlling what people ca nor cannot see. Trump suggested that Google's actions could be illegal and that the situation would be addressed. Google's stock price was down less than 1% on that day, and the market did not even respond through its traded volume. Later, Trump continued with accusations against Facebook, Twitter, and Google, saying that they are biased. Since these remarks are of a political nature, they were not further addressed.

Figure 9: Example of Trump's Tweet Sharing Already Reported News

Source: Trump (2017).

Appendix 2 contains a complete overview of the selected tweets for the ES application. The total sample of tweets with targeted firms includes only thirteen messages due to the following limitations:

- the time interval from November 8, 2016, until December 31, 2018;
- considered tweets had a strong sentiment and were mentioning companies;
- news outlets were excluded from the analysis;
- considered companies were listed either on NYSE or NASDAQ;
- messages had new information that was not already reported (Trump more often shared and commented news that was already publicly known (e.g., example in Figure 9); he rarely posted a new information; i.e., Trump was criticizing Rexnord regarding their announcement to move to Mexico, but the announcement was actually more than one-month-old news; Trump shared his appreciation for already-reported decisions from Apple, Ford, ExxonMobil, Walmart, Fiat Chrysler, Intel, and Novartis);
- and only one event per company was chosen on a larger time interval.

Due to the small sample of selected tweets, I applied the event study methodology to the whole sample of companies at once. Due to character limitation on Twitter, messages were sometimes posted over multiple tweets, which I considered as one event. Moreover, in cases when a tweet was posted after NYSE or NASDAQ trading hours on that day, it was considered that the market incorporated the tweet's information on the next trading day.

3.1.3 Tweets on Commodity Prices and Trade Negotiations

I reviewed what happened to currency exchange rates and commodity prices after Trump posted individual messages. Here, I did not use the event study methodology since the market model requires the use of appropriate benchmarks that I do not have in these cases.

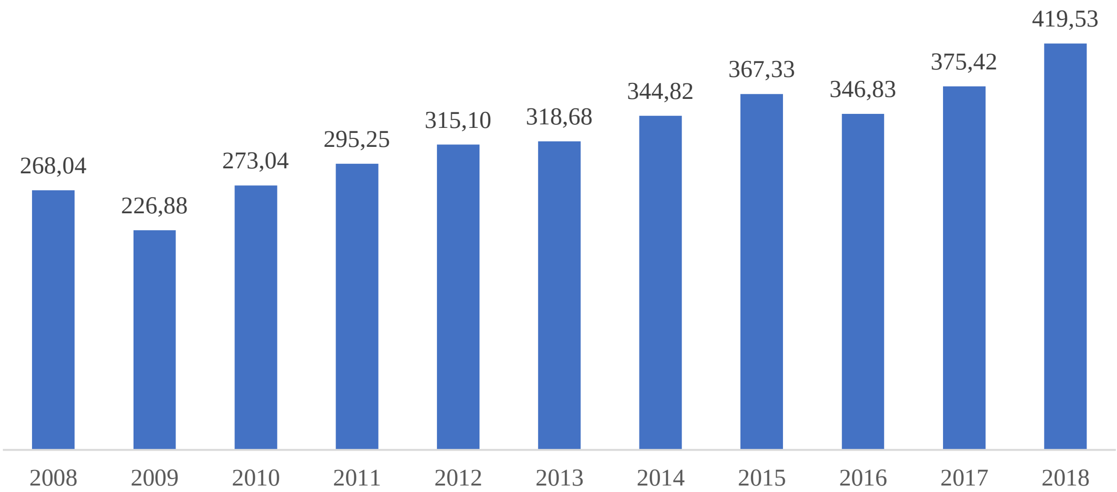
Mexico came under heavy criticism from Trump due to their lax control on Mexican emigration, and for attracting companies to its competitive labor market. In 2017, Trump started tweeting about trade agreements that the US holds with numerous countries and complained about how bad they are. On August 27, 2017, at 9:51 AM (EST), Trump wrote: *"We are in the NAFTA (worst trade deal ever made) renegotiation process with Mexico & Canada. Both being very difficult, may have to terminate?"* The agreement that was signed in December 1992 eliminated import tariffs on almost all traded goods between the three countries except for some agricultural goods. The next day after the tweet, the USD/MXN cross-rate increased by 1.49% and reached MXN 17.87 per USD 1. But, there was no significant change in the USD/CAD cross-rate. Trump had already threatened to terminate NAFTA earlier that year. However, this was the first time that Trump has complained about Canada's role.

US goods and services trade with Mexico totaled to an estimated USD 556.3 billion in 2017 (2018: USD 611.5 billion). Exports were USD 243.5 billion (2018: USD 265.4 billion), and imports were USD 312.8 billion (2018: USD 346.1 billion). Hence, a trade deficit with Mexico was USD 69.3 billion in 2017 (2018: USD 80.7 billion), and it was increasing every year from 2013 onwards (US Census Bureau, n.d.).

US goods and services trade with Canada totaled an estimated USD 581.6 billion in 2017 (2018: USD 618.6 billion). Exports were USD 282.5 billion (2018: USD 299.8 billion), and imports were USD 299.1 billion (2018: USD 318.8 billion). A trade deficit with Canada was USD 16.6 billion in 2017 (2018: USD 19.0 billion) (US Census Bureau, n.d.).

Besides a larger trade deficit with Mexico, we also have to take into consideration that on August 27, 2017, at 9:44 AM (EST), Trump also wrote: *"With Mexico being one of the highest crime Nations in the world, we must have the wall. Mexico will pay for it through reimbursement/other."* Mexico even responded to Trump's posts on the same day, through a press release, that they will not negotiate NAFTA nor any other aspect of the bilateral relationship through social media or any other news platform. While they pledged their negotiating position would continue to be constructive and serious, the Mexican peso still weakened.

Figure 10: Yearly US Trade Deficit with China since 2008 (in USD billion)



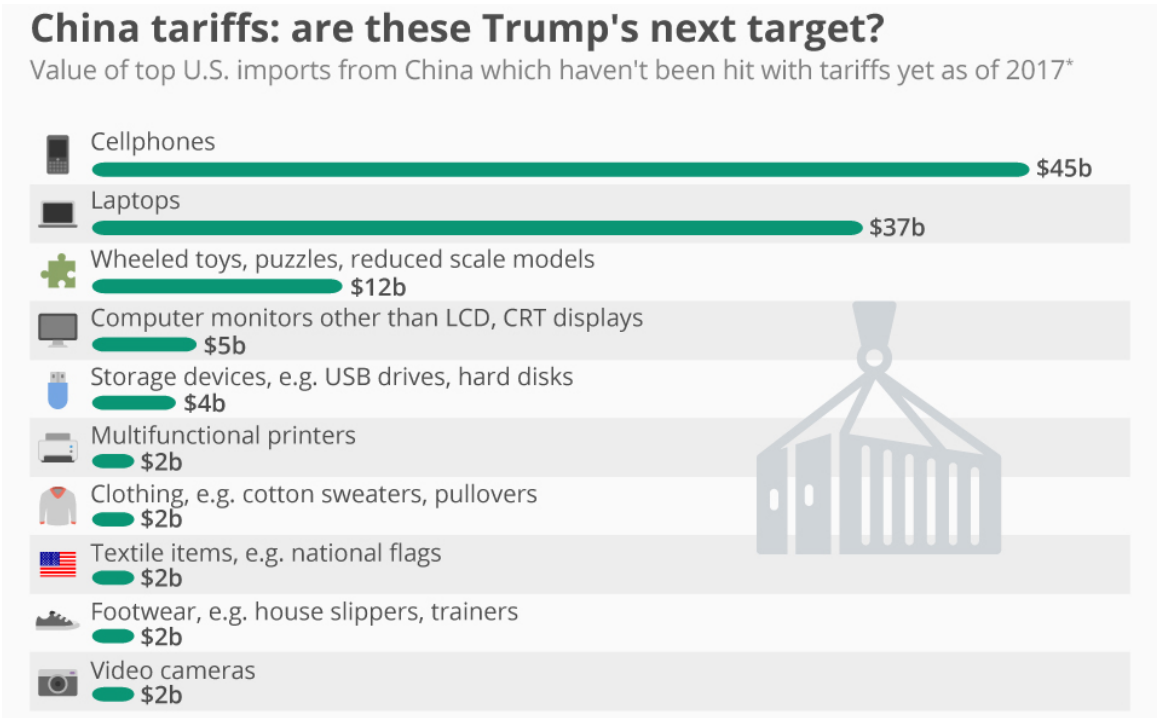
Source: US Census Bureau (n.d.).

One possible outcome of trade wars is currency devaluation. In the case of the US-China trade war, currency devaluation became the focus in late July 2018. The People's Bank of China set the reference rate to 6.7671 CNY to the USD. There was an immediate 0.9% drop from previous levels. US goods and services trade with China totaled an estimated USD 659.8 billion in 2018 (2017: USD 635.0 billion). Exports were USD 120.1 billion (2017: USD 129.8 billion), and imports were USD 539.7 billion (2017: 505.2 billion). Hence, a trade deficit with China was USD 419.5 billion in 2018 (2017: USD 375.4 billion) (US Census Bureau, n.d.).

Overall, the US had a trade deficit in the amount of USD 874.8 billion in 2018 (2017: USD 793.4 billion) (US Census Bureau, n.d.). Hence, almost half of it was due to the trade deficit with China. The US trade deficit with China from 2008 onwards is shown in Figure 10.

In November 2018, Trump said that the US was prepared to impose tariffs on all remaining Chinese products if he could not reach a deal with their president. The US has already imposed tariffs on USD 250 billion of Chinese goods. Figure 11 shows potential Chinese goods to which Trump could impose tariffs at the time.

Figure 11: Potential Chinese Goods for Tariffs as of 2017



Source: Blazyte (2018).

On December 2, 2018, at 11:00 PM (EST), Trump wrote: *"China has agreed to reduce and remove tariffs on cars coming into China from the US. Currently, the tariff is 40%."* The next day, the USD/CNY cross-rate decreased by 1.09% and reached 6.88 CNY per 1 USD.

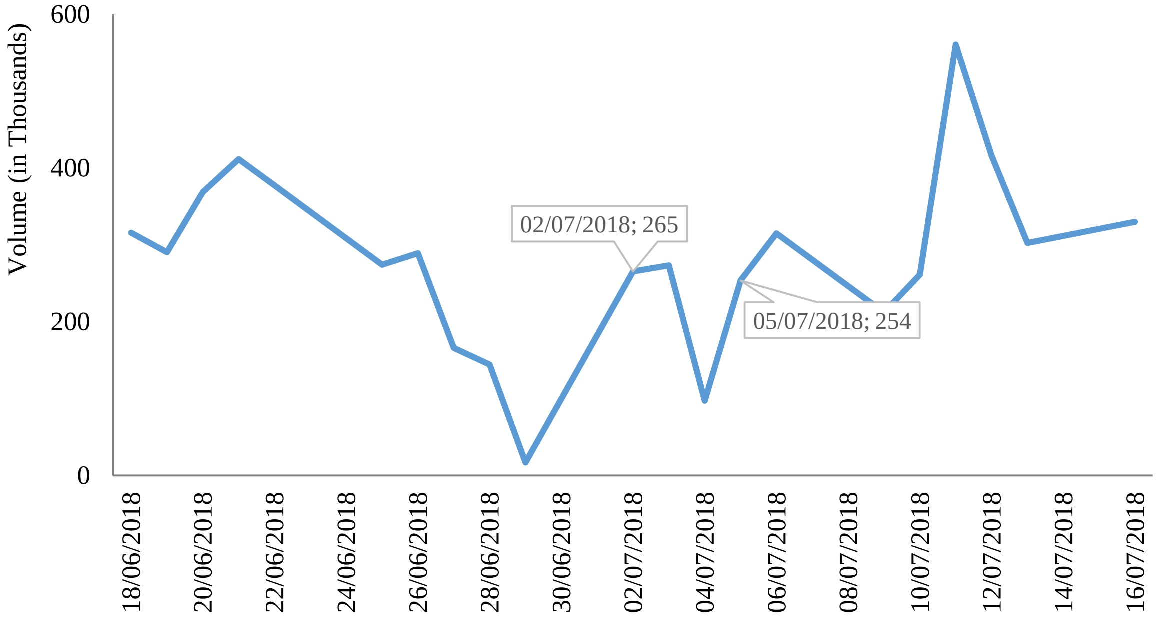
Besides Ford and Fiat Chrysler, German auto manufacturers also gain from a potential trade truce between the US and China. Both BMW and Daimler operate plants in the US, where they build SUVs and other luxury models that are also exported to China. Hence, the shares of BMW and Daimler rose after the tweet. Stocks of Chinese car dealers also increased in hopes that such a move could boost the domestic auto market (Reuters, 2018).

As of August 2019, negotiations between the US and China are still ongoing but have proven difficult. The US has imposed tariffs on more than USD 360 billion of Chinese goods, and China has responded with tariffs on more than USD 110 billion of US products. The two countries still have not reached an agreement, and the uncertainty is weighing on the global economy (BBC News, 2019).

In the summer of 2018, Trump complained about OPEC crude oil prices due to their increase. Summer months in the US usually lead to increased demand for oil, and that boosted the price of gasoline in a midterm election year. On Saturday, June 30, 2018, Trump wrote that he spoke to Saudi Arabia to increase the oil production capacity up to 2,000,000 barrels and that they agreed. The official statement from Saudi Arabia made no mention of an exact figure. The first trading day after Trump's tweet, Brent crude oil futures' price fell by 2.69% with increased trading volume.

A few days later, on July 4, 2018, at 4:46 PM (EST), Trump again took his dissatisfaction to Twitter: *"The OPEC Monopoly must remember that gas prices are up & they are doing little to help. If anything, they are driving prices higher as the United States defends many of their members for very little $'s. This must be a two-way street. REDUCE PRICING NOW!"* The next trading day, Brent crude oil futures' price was down by 1.09% with increased trading volume, which can be seen in Figure 12.

Figure 12: Trading Volume of CO1 Commodity around Trump's Posts



Source: Own work.

In 2019, Trump continued tweeting about crude oil. At the end of April, there was one of the most significant oil price drops in recent years, with WTI falling USD 2.41 per barrel. The decrease could have been influenced by Trump's tweet saying that he had spoken to Saudi Arabia about raising production to lower prices, and his remark that he had called up OPEC and told them to lower oil prices. There was not much evidence that Trump undertook any action other than his Twitter posts (Lynch, 2019).

3.2 ES Application: Reaction to Tweets on Publicly Traded Companies

Tweets were analyzed to assess the positive or negative sentiment of the statements regarding the targeted companies. Since the majority of Trump's posts had a negative sentiment, I selected those for the first part of the analysis. The alternative hypothesis I want to confirm is, therefore:

H_1: $Tweets\ with\ a\ negative\ sentiment\ lead\ to\ negative\ AR\ or\ AAR.$

Among the selected sample of tweets I used, in one case, the same tweet twice for testing on two different companies. Overall, there are twelve events for eleven different companies.[1] In the procedure, I used linear regression to calculate expected and abnormal returns for each company during the event window. As already mentioned, the length of the estimation window is 250 trading days. Coefficients and other statistical properties from the linear regression on each company are shown in Table 1.

Table 1: Linear Regression's Coefficients Included in Calculation of ARs

Company	Ticker	$\alpha_{returns}$	$\beta_{returns}$	R^2	F-statistic	p-value	$\sigma^2_{\varepsilon_i}$ estimate
The Boeing Company	BA	-0.0172	1.2297	0.4611	212.1891	0.0000	1.3789
Lockheed Martin Corporation	LMT	0.0692	0.4996	0.1650	48.9951	0.0000	0.9462
General Motors Company	GM	-0.1130	0.9497	0.2136	67.3726	0.0000	2.8356
Harley-Davidson, Inc.	HOG	-0.1178	0.7518	0.1273	36.1773	0.0000	2.3898
Toyota Motor Corporation	TM	-0.0553	1.1241	0.3961	162.6518	0.0000	1.3299
Merck & Co., Inc.	MRK	-0.0548	0.6670	0.1806	54.6481	0.0000	1.2585
Pfizer Inc.	PFE	-0.0060	0.8266	0.4266	184.4991	0.0000	0.5726
Nordstrom, Inc.	JWN	-0.1369	1.1924	0.1190	33.4919	0.0000	5.3755
Amazon.com, Inc.[2]	AMZN	0.0409	1.1697	0.2426	79.4400	0.0000	1.0925
Wells Fargo & Company	WFC	-0.0951	1.5371	0.3552	136.5895	0.0000	0.8106
Amazon.com, Inc.[3]	AMZN	0.1701	1.2270	0.3424	129.1157	0.0000	1.8219
Alphabet Inc.	GOOGL	0.0183	1.4165	0.6008	373.1672	0.0000	0.8304

Source: Own work.

The market proxy used is S&P500, since in a situation when we have an analysis over a large number of stocks from different industries, it is more reasonable to stick to a broader market index. As stated under methodology, $R_{i\tau}$ and $R_{m\tau}$ are the period τ returns on asset i and the market portfolio. α_i, β_i, and $\sigma^2_{\varepsilon_i}$ are the respective parameters. For any asset i, the market model is:

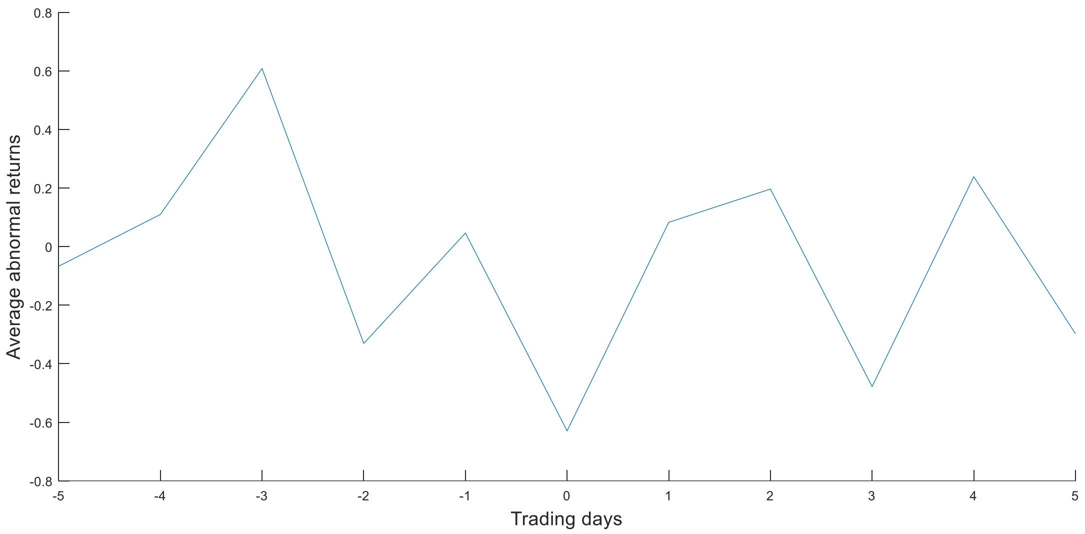
[1] AMZN data was used twice since the events were almost one year apart.
[2] Tweeted on 16/08/2017.
[3] Tweeted on 23/07/2018.

$$R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{i\tau},$$

where $E[\varepsilon_{i\tau}] = 0$ and $VAR[\varepsilon_{i\tau}] = \sigma^2_{\varepsilon_i}$.

A benefit when using the market model depends on the R^2 from the regression. The higher R^2 means a better model. The results in Table 1 show that the quality of the market model application differs between companies; R^2 moves on an interval from 0.1190 to 0.6008. The reasoning behind this could be that it is difficult to apply a good market proxy for such a wide range of industries.

Figure 13: AARs (at 0 the Event Date)



Source: Own work.

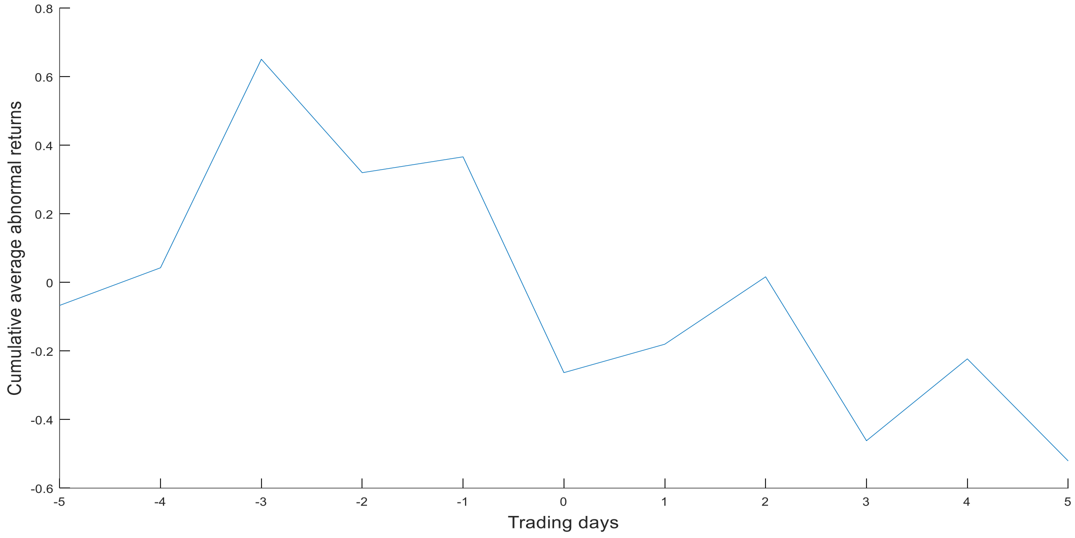
From Figure 13, it is evident that, on the event date, AAR was the lowest due to negative remarks Trump made via Twitter (i.e., he negatively affected the stock's price), but since there are also other negative deviations in the event window, it is not yet clear whether the result will be statistically significant.

From Figure 14, it can be seen that CAAR decreased on the event day and also continued decreasing in the following days.

Statistical properties of the data on AARs are as follows:

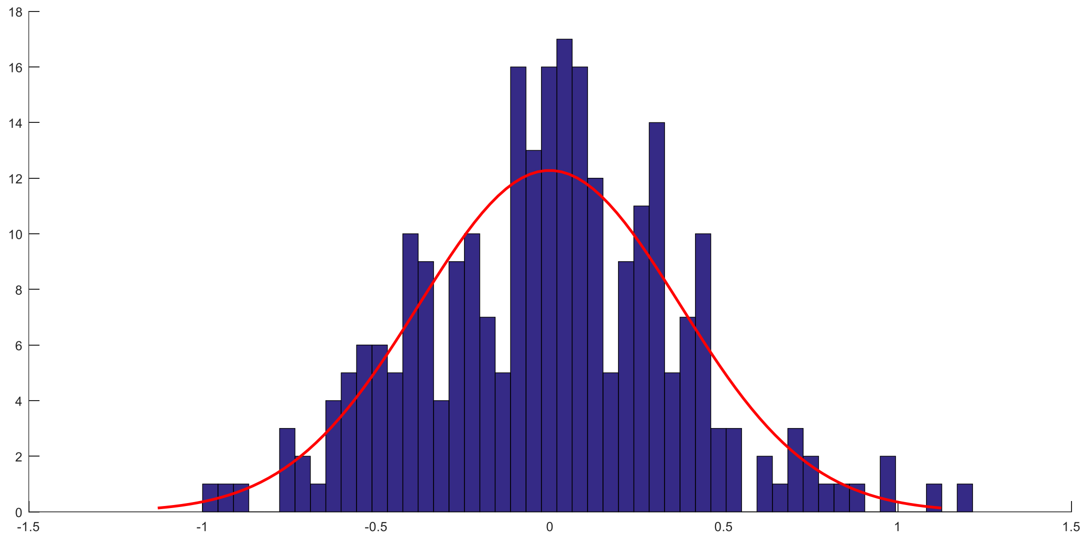
- mean at -0.0020,
- median at 0.0162,
- and variance at 0.1411.

Figure 14: CAARs (at 0 the Event Date)



Source: Own work.

Figure 15: Histogram with a Normal Distribution Fit on AARs



Source: Own work.

The results of fitting a normal density function on data are presented in Figure 15. Hence, the use of parametric tests for the null hypothesis testing is appropriate. As already described, the null hypothesis (i.e., H_0) suggests that there are no ARs within the event day or window. The sign test requires that the expected proportion of negative abnormal returns under the null hypothesis is 0.5 since it is equally probable that the returns will be negative or positive.

As shown in Table 2, I tested the null hypothesis for the event day only, since it is not expected that the information will have a lasting effect on the stock's price. Also, the assumption is that information did not reach the market before Trump posted it. All tests confirmed that, at a 5% significance level, tweets with a negative sentiment lead to the negative AR or AAR.

Table 2: Significance Tests Results (H_0: $AR_{i\tau} = 0$ or H_0: $p \leq 0.5$)

Test	Type	Test statistic	p-value
BMP Test	Parametric	-2.4411	0.0146
Patell Test	Parametric	-2.4200	0.0155
Sign Test	Nonparametric	2.8868	0.0039

Source: Own work.

The traded volume can also be a good indicator of "abnormal activity" on the market. We can assume that when the market receives new information, it will incorporate it in negative or positive price movements, and at the same time, it will significantly increase the trading volume on the individual stocks. The alternative hypothesis, in this case, is:

H_1: *Tweets with a negative or positive sentiment lead to positive AV or AAV.*

Table 3: Linear Regression's Coefficients Included in Calculation of AVs

Company	Ticker	α_{volume}	β_{volume}	R^2	F-statistic	p-value	$\sigma^2_{\varepsilon_i}$ estimate
The Boeing Company	BA	-9.4846	1.1263	0.4519	204.4311	0.0000	0.0986
Lockheed Martin Corporation	LMT	8.0750	0.2493	0.0110	2.7555	0.0982	0.3640
General Motors Company	GM	-7.8913	1.0657	0.4124	174.0689	0.0000	0.1034
Harley-Davidson, Inc.	HOG	0.0390	0.6959	0.1126	31.4631	0.0000	0.2180
Toyota Motor Corporation	TM	-5.7233	0.7724	0.1372	39.4259	0.0000	0.2318
Ford Motor Company	F	-4.5245	0.8948	0.3032	107.8957	0.0000	0.1194
Merck & Co., Inc.	MRK	-6.5107	0.9594	0.3426	129.2189	0.0000	0.1031
Pfizer Inc.	PFE	-7.6014	1.0052	0.4673	217.5512	0.0000	0.0660
Nordstrom, Inc.	JWN	0.3663	0.6953	0.1101	30.6901	0.0000	0.2118
Amazon.com, Inc.[4]	AMZN	-3.4722	0.8404	0.2281	73.2957	0.0000	0.1189
Wells Fargo & Company	WFC	-2.3752	0.7534	0.2378	77.3927	0.0000	0.0886
Amazon.com, Inc.[5]	AMZN	-5.4722	0.9474	0.2743	93.7355	0.0000	0.1362
Alphabet Inc.	GOOGL	-5.5457	0.9338	0.3512	134.2207	0.0000	0.0931

Source: Own work.

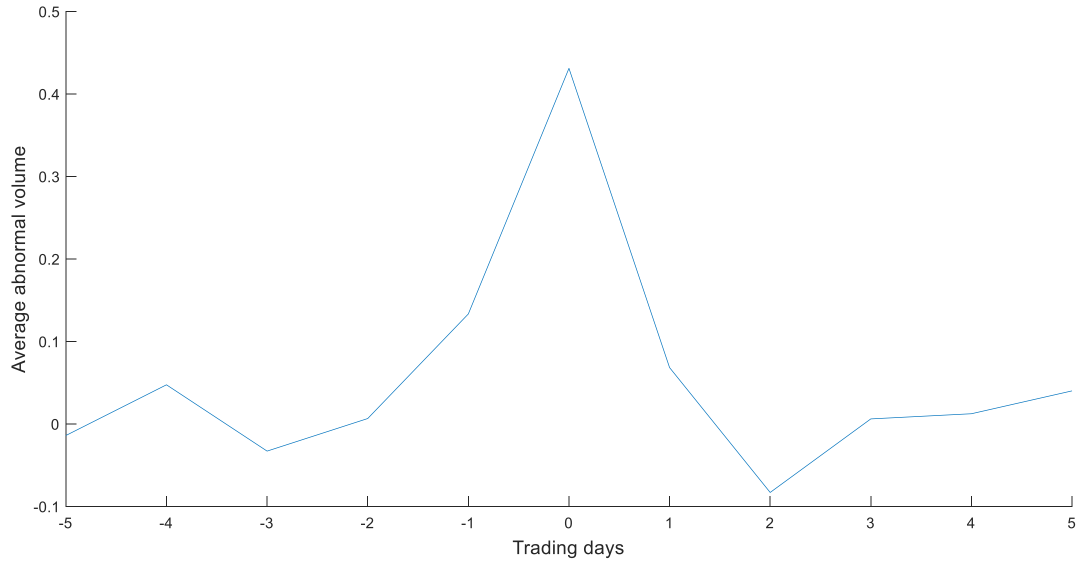
As already described, I used the log-transformed relative volume per company. I took S&P500 volume as a market proxy and all selected tweets with a negative or positive

[4] Tweeted on 16/08/2017
[5] Tweeted on 23/07/2018

sentiment.[6] Overall, there are thirteen events for twelve different companies.[7] Coefficients and other statistical properties from the linear regression on each company are shown in Table 3.

From the results in Table 3, it can be seen that the quality of the market model application differs between companies, R^2 moves on an interval from 0.0110 to 0.4673.

Figure 16: AAVs (at 0 the Event Date)



Source: Own work.

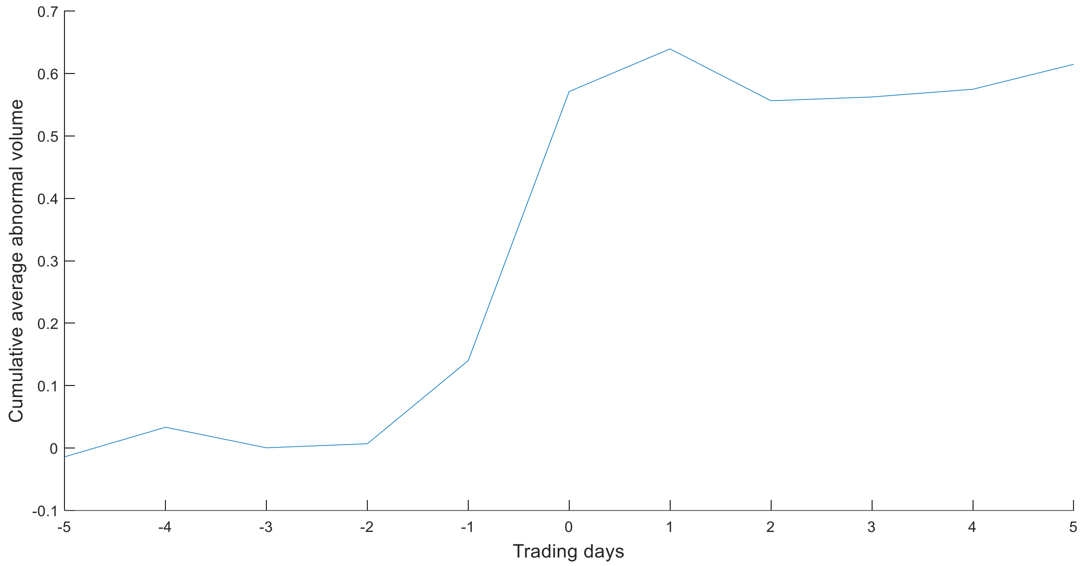
From Figure 16 and Figure 17, it can be seen that on the event date, AAV and CAAV increased significantly due to negative or positive remarks Trump made via Twitter. As it seems, the volume can sometimes be an even better indicator of the market's response to the news.

Results of fitting a normal density function on data are presented in Figure 18. Statistical properties of the data on AAVs are as follows:

- mean at 0.0024,
- median at -0.0090,
- and variance at 0.0133.

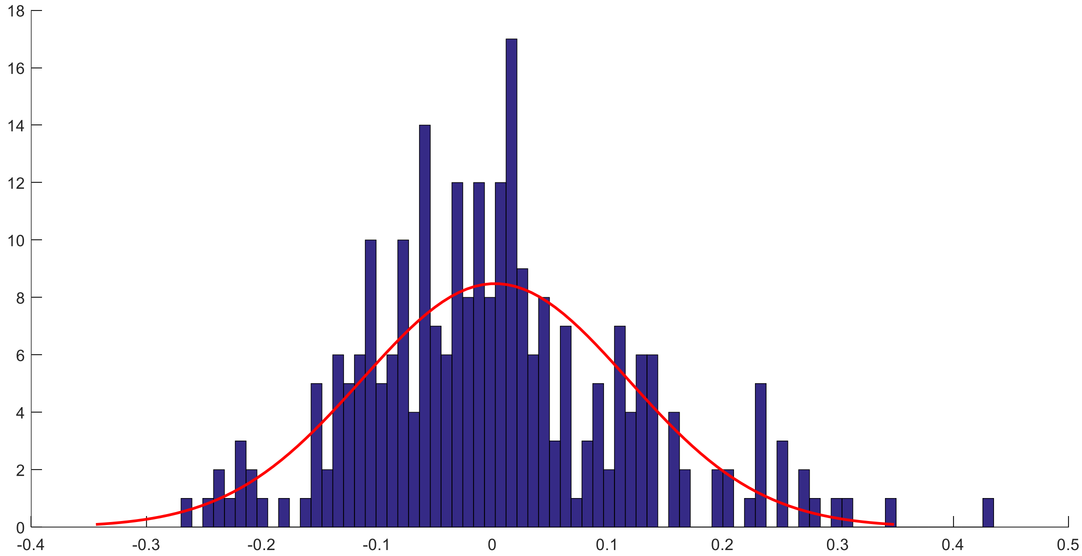
[6] I simplified the procedure by taking the logarithm on index volume data directly, without any transformation based on outstanding shares of stocks that are included in the index basket.
[7] AMZN data was used twice since the events were almost one year apart.

Figure 17: CAAVs (at 0 the Event Date)



Source: Own work.

Figure 18: Histogram with a Normal Distribution Fit on AAVs



Source: Own work.

The null hypothesis (i.e., H_0) suggests that there are no AVs within the event day or window. The sign test requires that the expected proportion of positive abnormal volume under the null hypothesis is 0.5 since it is equally probable that the abnormal volume will be negative or positive. Similarly, I tested the null hypothesis for the event day only. As shown in Table 4, all tests confirmed, at a 5% significance level, that tweets with a negative or positive sentiment lead to positive AV or AAV.

Table 4: Significance Tests Results (H_0: $AV_{i\tau} = 0$ or H_0: $p \leq 0.5$)

Test	Type	Test statistic	p-value
BMP Test	Parametric	4.0697	0.0000
Patell Test	Parametric	3.7079	0.0002
Sign Test	Nonparametric	2.4961	0.0126

Source: Own work.

3.3 PCA Application: Systematic Risk in US Automotive Industry

Besides already selected four tweets that targeted individual companies in the automotive industry, I added to this review eight new tweets that mentioned the industry itself. An overview of selected Trump's tweets can be found in Appendix 3. The selected stocks for the principal component analysis are listed either on NYSE or NASDAQ (Table 5).

Table 5: List of Selected Stocks in the US Automotive Industry

Nr.	Company	Ticker	Market
1	Federal Signal Corporation	FSS	NYSE
2	Fiat Chrysler Automobiles N.V.	FCAU	NYSE
3	Ford Motor Company	F	NYSE
4	General Motors Company	GM	NYSE
5	Harley-Davidson, Inc.	HOG	NYSE
6	Honda Motor Co., Ltd.	HMC	NYSE
7	Kandi Technologies Group, Inc.	KNDI	NASDAQ
8	Navistar International Corporation	NAV	NYSE
9	Oshkosh Corporation	OSK	NYSE
10	PACCAR Inc.	PCAR	NASDAQ
11	Spartan Motors, Inc.	SPAR	NASDAQ
12	Tata Motors Limited	TTM	NYSE
13	Tesla, Inc.	TSLA	NASDAQ
14	Toyota Motor Corporation	TM	NYSE
15	WABCO Holdings Inc.	WBC	NYSE
16	Workhorse Group Inc.	WKHS	NASDAQ

Source: Own work.

Since there are not many big vehicle manufacturers in the US, I included in the sample as many stocks as possible even if they do not have the majority of their industry in the US. In order to get better results, the criterion for selection was that the stock from the mentioned industry should be listed on the US markets.

Dow Jones US Automobiles Index (DJUSAU) consists of four major American companies: Harley-Davidson, Ford, General Motors, and Tesla. From Figure 19, it can be seen that DJUSAU started underperforming S&P500 even before Trump's election and is still not growing enough to catch up.

Figure 19: DJUSAU Index Performance since January 1, 2008

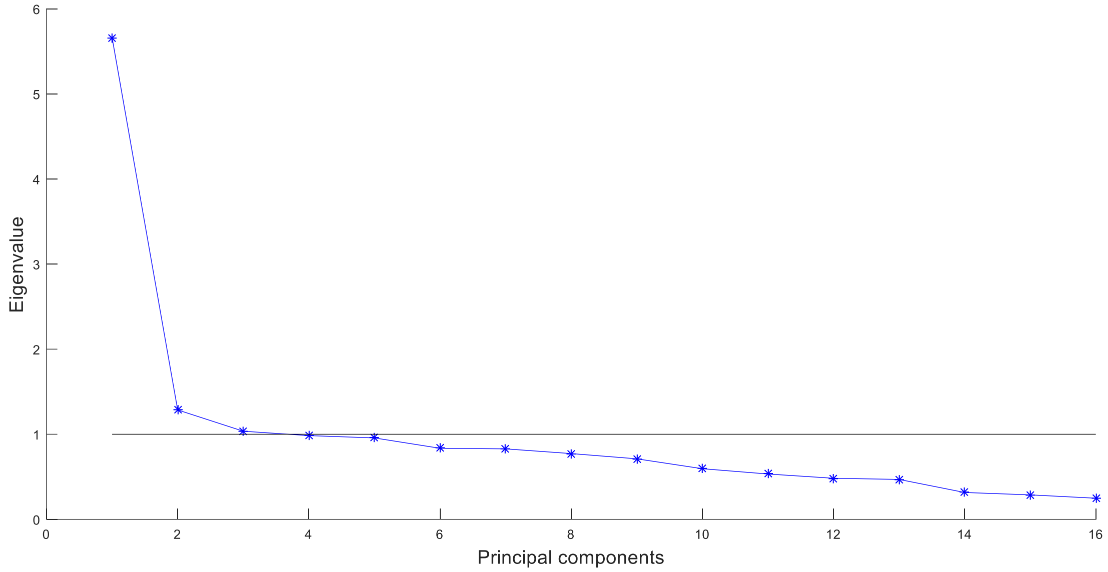
Source: Own work.

Since the beginning of 2016, the automotive industry underperformed the broader market. During the election campaign, Trump often criticized Ford's announcement for moving its small-car production to Mexico. Trump started the first presidential debate by criticizing Ford for taking jobs from the US. The automotive industry is one of the key beneficiaries of free trade agreements such as NAFTA. Trump's intention during the election campaign to scrap many existing trade policies were not favorable for automakers (Parashar, 2016).

This part of the analysis aimed to determine if the factor structure changed through Trump's presidency. Firstly, I calculated returns for stocks that represent the US automotive industry and then did the augmented Dickey-Fuller test for stationarity. The results showed that data is stationary, so there was no need for differentiation. I standardized the returns (i.e., with mean 0 and standard deviation 1) and then used already integrated Matlab's function *pca* to get the eigenvalues and corresponding explained variance.

Over the whole sample of sixteen stocks from January 1, 2016, until December 31, 2018, there are only three eigenvalues that are above one, as shown in Figure 20.

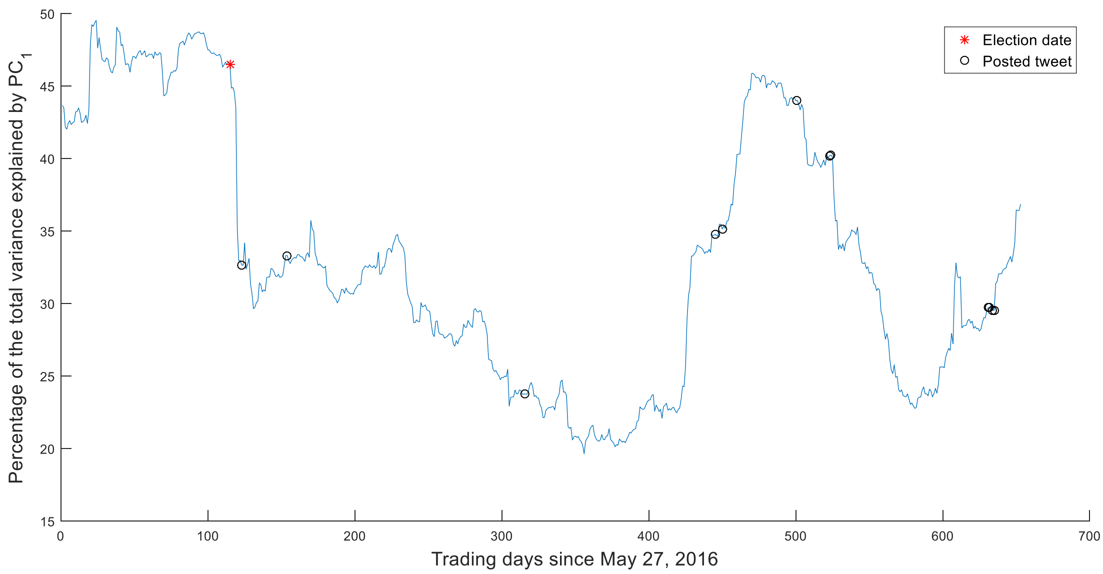
Figure 20: Eigenvalues for Sixteen Stocks in Automotive Industry



Source: Own work.

As already described, the first principal component represents the systematic risk that cannot be diversified away. Hence, I was monitoring the time evolution only of the first principal component and how much of the total variance it can explain through time. With a loop that takes the previous one hundred trading days into a calculation of the principal components, I prepared a visualization of how much of the total variance PC_1 can explain through time. In Figure 21, it can be seen how the systematic risk evolved through time since Trump was elected and in times when he was tweeting about the automotive industry.

Figure 21: Percentage of the Total Variance Explained by PC_1



Source: Own work.

The systematic risk decreased significantly in the automotive industry after Trump's election, and it was further decreasing when Trump started threatening American manufacturers with taxes if they decided to move their plants to other countries.

At the start of 2018, as a response to steel tariffs, the EU threatened to target US imports such as Harley-Davidson motorbikes, which might have initiated the significant increase of the systematic risk in the US automotive industry. On March 3, 2018, at 12:53 PM (EST), Trump wrote: *"If the EU wants to further increase their already massive tariffs and barriers on US companies doing business there, we will simply apply a Tax on their Cars which freely pour into the US. They make it impossible for our cars (and more) to sell there. Big trade imbalance!"* He has escalated the threat of a trade war with the EU with the warning that the US will impose taxes on their cars.

Three months later, the systematic risk started falling again, and on May 23, 2018, at 9:18 AM (EST), Trump tweeted: *"There will be big news coming soon for our great American Autoworkers. After many decades of losing your jobs to other countries, you have waited long enough!"* In negotiating an update to the NAFTA agreement, vehicle trade has been one of the largest complications. Trump has threatened to throw away a two-decades-old agreement. When reporters asked him about NAFTA agreement and auto manufacturers, he answered that US auto workers would be satisfied with the results of negotiations.

At the end of November 2018, Trump was upset with General Motors' decision to close some American plants, and he was again making threats with tariffs. The systematic risk has increased since then.

We can conclude that Trump's decisions and threats were involved in the evolution of the systematic risk for the automotive industry, but from the performed analysis, it is not possible to explain the extent to which that was the driver. Thus, there is a potential to go further with the analysis and try using linear regression to establish the drivers behind the increasing or decreasing systematic risk.

CONCLUSION

The total number of people that follow Trump's Twitter profile has increased substantially since he became the president. At the end of 2018, Trump had a total of 56.7 million followers. This increase included a broader base of followers and, accordingly, the range in sentiment widened significantly, with a lot more negative responses to his tweets.

For my selected group, I chose the most influential tweets after Trump's election, which highlights the first limitation of this research; that is, bias due to subjectivity. The tweets were analyzed by assessing the sentiment (positive or negative) of the statements regarding the targeted companies. Since the majority of Trump's posts had a negative sentiment, I selected only these for the first part of the analysis. The total sample included twelve events, which were announced via Twitter. A smaller sample size brings out the second limitation of this research. Therefore, the conclusion cannot explain the overall impact of his posts, but it can only suggest an answer if his posts can sometimes leave consequences on the markets. All tests confirmed that at a 5% significance level, tweets with a negative sentiment led to the negative AR or AAR on the event day.

Moreover, I tested if tweets could lead to positive AV or AAV. When the market receives new information, it will incorporate it in negative or positive price movements, and at the same time, it will increase the trading volume on the individual stocks. The total sample included thirteen events. It was quickly clear from the data that on the event date, AAV and CAAV increased significantly due to negative or positive remarks Trump made. All tests confirmed at a 5% significance level that tweets with a negative or positive sentiment led to positive AV or AAV on the event day.

Hence, it is undeniable that Trump's tweets have the potential to inflate the short-term volatility of some corporate equities. However, Trump cannot influence stock prices in the long run. It seems that markets incorporate tweets as noise that has a temporal impact and is only relevant to the high-frequency traders. The companies and their long-term investors care more about the impact on the firm's value in the long-run. Overall, it should be once more noted that, despite the effort, results might be contaminated by other events besides Trump's tweets since the news on an individual company might become public via different sources simultaneously. Since this research used only daily data, it could not focus directly on posts' effects that lasted very shortly. This brings out the third limitation of the research regarding event studies.

It can be noted that markets are quite sensitive to Trump's tweets about government contractors since they create speculation if any contracts might be voided or new ones signed. A strong case that confirms that was when Lockheed Martin's stock price fell by 2.5% towards the end of the trading day after the tweet. Moreover, stock trading volume spiked when the market received the information.

From the review of the data, it also does not seem that Trump's posts would have any significant impact on currency exchange rates or commodity markets, at least not in the long run. In the case of the US and China trade war, currency devaluation became the focus in late July 2018. A trade deficit with China was USD 419.5 billion in 2018 (2017: USD 375.4 billion) (US Census Bureau, n.d.). Trump also complained a lot about crude oil prices. At the end of April 2019, there was one of the most significant oil price drops in recent years that could be at least partially influenced by Trump's tweet, with WTI falling to USD 2.41 per barrel.

The automotive industry was often Trump's focus on Twitter. The results showed that the systematic risk decreased significantly in the automotive industry after Trump's election, and it was further decreasing when Trump started threatening American manufacturers with taxes if they decide to move their plants to other countries. At the start of 2018, as a response to steel tariffs, the EU threatened to target US imports such as Harley-Davidson motorbikes. That might have initiated a significant increase in the systematic risk in the US automotive industry. However, from the performed analysis, it is not possible to explain to what extent Trump's threats or tweets were the drivers. The limitation of a small sample size that represents the US automotive industry also applies here.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene Language)

Število Trumpovih sledilcev na Twitterju se je od začetka njegovega mandata močno povečalo, konec leta 2018 jih je imel kar 56,7 milijona. Večje število sledilcev pa je vplivalo tudi na več negativnih odzivov. Twitter je spletna platforma, kjer lahko uporabniki objavljajo sporočila (t. i. »tvite«) in sledijo ljudem, ki jih zanimajo.

Obdobje za analizo tvitov je bilo izbrano od Trumpove izvolitve, tj. 8. 11. 2016, do 31. 12. 2018. Metodologijo študije dogodka sem uporabila na 12 primerih tvitov, za katere je bil pričakovan negativen odziv na trgu delnic. Manjša velikost vzorca in subjektivnost pri izboru tvitov predstavljata omejitev te raziskave, ki tako ne nosi pomembnih rezultatov za vse objavljene tvite. Ničelna hipoteza za testiranje statistične značilnosti je bila, da tviti z negativnim sporočilom ne vodijo do negativnih nenormalnih donosov. Hipoteza je bila zavrnjena pri 5-odstotni stopnji značilnosti.

Na 13 primerih tvitov sem dodatno testirala, ali objave povečajo obseg trgovanja. Na datum dogodka sta se povprečni nenormalni obseg trgovanja (angl. AAV) in kumulativni povprečni nenormalni obseg trgovanja (angl. CAAV) znatno povečala. Ničelna hipoteza, da tviti z negativnim ali pozitivnim sporočilom ne vodijo do povečanega obsega trgovanja, je bila zavrnjena pri 5-odstotni stopnji značilnosti. Izbrani vzorec Trumpovih tvitov je vplival na trg delnic, a le kratkoročno. Glede na to, da tviti pogosto vsebujejo kritiko ali nepodprte informacije, je razumljivo, da trg sprejme tvit kot hrup, ki sicer nima dolgoročnega vpliva in je pomemben le pri visokofrekvenčnem trgovanju.

Iz analize podatkov tudi ni videti, da bi Trumpove objave imele pomemben vpliv na menjalne tečaje ali trge z blagom, vsaj ne dolgoročno. Na primeru trgovinske vojne med ZDA in Kitajsko je devalvacija valut postala osrednja tema pogovora konec julija 2018. Trgovinski primanjkljaj s Kitajsko je bil v letu 2018 419,5 milijarde USD (2017: 375,4 milijarde USD) (US Census Bureau, n.d.). Trump se je na Twitterju veliko pritoževal tudi nad cenami surove nafte. Konec aprila 2019 je prišlo do enega najpomembnejših padcev cen nafte v zadnjih letih, ko je WTI padel za 2,41 USD na sod, na kar je vsaj deloma vplival tudi njegov tvit.

Avtomobilska industrija je bila pogosto tarča Trumpovih objav na Twitterju. Z metodo glavnih komponent sem želela ugotoviti, ali se je faktorska struktura spremenila v času Trumpovega predsedovanja. Rezultati so pokazali, da se je sistematično tveganje v avtomobilski industriji po Trumpovi izvolitvi močno zmanjšalo in se je še naprej zmanjševalo, ko je Trump ameriškim proizvajalcem grozil z davki v primeru, če se bodo odločili preseliti svoje tovarne v druge države. V začetku leta 2018 je EU odgovorila na carine za jeklo z opozorilom, da bo uvedla višje carine na uvoz motornih koles Harley-Davidson. To je verjetno vplivalo na povečanje sistematičnega tveganja v avtomobilski industriji v ZDA. Iz izvedene analize ni mogoče razložiti, v kakšnem obsegu so na sistematično tveganje vplivale Trumpove grožnje ali tviti.

Appendix 2: Overview of the Selected Tweets for Analysis in 3.2

Date	Time (EST)	Ticker	Tweet Text	Market	Sentiment
17/11/2016	9:01 PM	F	Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico	NYSE	Positive
06/12/2016	8:52 AM	BA	Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!	NYSE	Negative
12/12/2016	8:26 AM	LMT	The F-35 program and cost is out of control. Billions of dollars can and will be saved on military (and other) purchases after January 20th.	NYSE	Negative
05/01/2017	1:14 PM	TM	Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for US. NO WAY! Build plant in US or pay big border tax.	NYSE	Negative
08/02/2017	10:51 AM	JWN	My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!	NYSE	Negative
16/08/2017	6:12 AM	AMZN	Amazon is doing great damage to tax paying retailers. Towns, cities and states throughout the US are being hurt - many jobs being lost!	NASDAQ	Negative
08/12/2017	10:18 AM	WFC	Fines and penalties against Wells Fargo Bank for their bad acts against their customers and others will not be dropped, as has incorrectly been reported, but will be pursued and, if anything, substantially increased. I will cut Regs but make penalties severe when caught cheating!	NYSE	Negative
11/05/2018	3:30 PM	MRK	Today, my Administration is launching the most sweeping action in history to lower the price of prescription drugs for the American People. We will have tougher negotiation, more competition, and much lower prices at the pharmacy counter!	NYSE	Positive
25/06/2018	5:28 PM	HOG	Surprised that Harley-Davidson, of all companies, would be the first to wave the White Flag. I fought hard for them and ultimately they will not pay tariffs selling into the EU, which has hurt us badly on trade, down $151 Billion. Taxes just a Harley excuse - be patient! #MAGA	NYSE	Negative

Date	Time (EST)	Ticker	Tweet Text	Market	Sentiment
09/07/2018	1:08 PM	PFE MRK	Pfizer & others should be ashamed that they have raised drug prices for no reason. They are merely taking advantage of the poor & others unable to defend themselves, while at the same time giving bargain basement prices to other countries in Europe & elsewhere. We will respond!	NYSE	Negative
23/07/2018	9:21 AM 9:35 AM	AMZN	The Amazon Washington Post has gone crazy against me ever since they lost the Internet Tax Case in the US Supreme Court two months ago. Next up is the US Post Office which they use, at a fraction of real cost, as their "delivery boy" for a BIG percentage of their packages.... ....In my opinion the Washington Post is nothing more than an expensive (the paper loses a fortune) lobbyist for Amazon. Is it used as protection against antitrust claims which many feel should be brought?	NASDAQ	Negative
28/08/2018	11:02 AM	GOOGL	Google search results for "Trump News" shows only the viewing/reporting of Fake News Media. In other words, they have it RIGGED, for me & others, so that almost all stories & news is BAD. Fake CNN is prominent. Republican/Conservative & Fair Media is shut out. Illegal? 96% of.... ....results on "Trump News" are from National Left-Wing Media, very dangerous. Google & others are suppressing voices of Conservatives and hiding information and news that is good. They are controlling what we can & cannot see. This is a very serious situation-will be addressed!	NASDAQ	Negative
27/11/2018	2:05 PM	GM	Very disappointed with General Motors and their CEO, Mary Barra, for closing plants in Ohio, Michigan and Maryland. Nothing being closed in Mexico & China. The US saved General Motors, and this is the THANKS we get! We are now looking at cutting all @GM subsidies, including.... ....for electric cars. General Motors made a big China bet years ago when they built plants there (and in Mexico) - don't think that bet is going to pay off. I am here to protect America's Workers!	NYSE	Negative

Appendix 3: Overview of the Selected Tweets for Analysis in 3.3

Date	Time (EST)	Tweet Text	Industry
17/11/2016	9:01 PM	Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico	Automotive
05/01/2017	1:14 PM	Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for US. NO WAY! Build plant in US or pay big border tax.	Automotive
27/08/2017	9:51 AM	We are in the NAFTA (worst trade deal ever made) renegotiation process with Mexico & Canada. Both being very difficult, may have to terminate?	Automotive
03/03/2018	12:53 PM	If the EU wants to further increase their already massive tariffs and barriers on US companies doing business there, we will simply apply a Tax on their Cars which freely pour into the US. They make it impossible for our cars (and more) to sell there. Big trade imbalance!	Automotive
10/03/2018	4:29 PM	The European Union, wonderful countries who treat the US very badly on trade, are complaining about the tariffs on Steel & Aluminum. If they drop their horrific barriers & tariffs on US products going in, we will likewise drop ours. Big Deficit. If not, we Tax Cars etc. FAIR!	Automotive
23/05/2018	9:18 AM	There will be big news coming soon for our great American Autoworkers. After many decades of losing your jobs to other countries, you have waited long enough!	Automotive
22/06/2018	8:34 PM	Based on the Tariffs and Trade Barriers long placed on the US & its great companies and workers by the European Union, if these Tariffs and Barriers are not soon broken down and removed, we will be placing a 20% Tariff on all of their cars coming into the US. Build them here!	Automotive
25/06/2018	5:28 PM	Surprised that Harley-Davidson, of all companies, would be the first to wave the White Flag. I fought hard for them and ultimately they will not pay tariffs selling into the EU, which has hurt us badly on trade, down $151 Billion. Taxes just a Harley excuse - be patient! #MAGA	Automotive
27/11/2018	2:05 PM	Very disappointed with General Motors and their CEO, Mary Barra, for closing plants in Ohio, Michigan and Maryland. Nothing being closed in Mexico & China. The US saved General Motors, and this is the THANKS we get! We are now looking at cutting all @GM subsidies, including.... ....for electric cars. General Motors made a big China bet years ago when they built plants there (and in Mexico) - don't think that bet is going to pay off. I am here to protect America's Workers!	Automotive

Date	Time (EST)	Tweet Text	Industry
28/11/2018	9:43 AM 9:49 AM	The reason that the small truck business in the US is such a go to favorite is that, for many years, Tariffs of 25% have been put on small trucks coming into our country. It is called the "chicken tax." If we did that with cars coming in, many more cars would be built here..... .....and G.M. would not be closing their plants in Ohio, Michigan & Maryland. Get smart Congress. Also, the countries that send us cars have taken advantage of the US for decades. The President has great power on this issue - Because of the G.M. event, it is being studied now!	Automotive
30/11/2018	9:45 AM	Just signed one of the most important, and largest, Trade Deals in US and World History. The United States, Mexico and Canada worked so well together in crafting this great document. The terrible NAFTA will soon be gone. The USMCA will be fantastic for all!	Automotive
02/12/2018	11:00 PM	China has agreed to reduce and remove tariffs on cars coming into China from the US. Currently the tariff is 40%.	Automotive