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The Impact of Trump's Tweets on U.S. Financial Returns

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Abstract

In this study, we investigate whether U.S. President, Donald Trump's Twitter sentiment and activity affect financial markets. By employing the event study methodology, we provide strong empirical evidence that our small-cap portfolios and selected sample firms have been affected by Trump's Twitter sentiment. Overall, we find that positive sentiment tweets generate positive abnormal returns, whereas negative sentiment tweets generate negative abnormal returns. The effect persists multiple days after the announcement date for several of the sample firms, which is considered a violation of the semi-strong form of the efficient market hypothesis (EMH). The portfolios are consistent with the EMH for positive tweets, as the effect is rapidly incorporated (within one day). For negative tweets, the EMH is violated, as the cumulative average abnormal returns (CAAR) continue to drift after the event. This indicates that the market finds it more challenging to value negative Trump sentiment than positive Trump sentiment. Moreover, we find that Trump's Twitter sentiment affects stocks across all sizes and multiple industries in our sample. Further, our secondary study provides empirical evidence that Trump's tweet frequency also affects the sample portfolios. This effect persists over multiple days and accordingly violates the EMH. Lastly, we present complementary findings regarding volume traded, market volatility, and the variability in the effect of Trump's tweets over time.

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1 Introduction

Several studies have provided empirical evidence suggesting that anomalies in financial markets can be explained by social media behaviour. Bollen, Mao and Zeng (2011) and Luo, Zhang and Duan (2013) provide evidence that securities' value moves more than their fundamentals would suggest, and that these anomalies can be traced to social media activity. Bollen et al. (2011) find that public sentiment obtained from large-scale Twitter feeds predict movements in the Dow Jones Industrial Index (DJIA). Luo et al. (2013) argue that social media metrics predict firm equity values. Today there is a broad acceptance concerning the notion that social media can significantly impact a firm's reputation, sales or even survival (Kietzmann, Hermkens, McCarthy & Silvestre, 2011). As our digital sharing and connectivity increases, our behaviours, relations, and activity become more quantified and measurable. This ever-increasing digital footprint allows us to examine the impact of public opinion, human behaviour, and social media on financial markets. Moreover, to an increasing extent, firms today need to understand critical elements of the social media landscape, including who some of the main influencers are (Kietzmann et al., 2011). In many ways, the new digital era which we currently find ourselves in has added a new risk dimension for companies.

In this study, we will investigate whether U.S. President, Donald Trump's Twitter sentiment and activity affect U.S. financial returns. Donald Trump was elected the 45th President of the United States on November 8, 2016, and has approximately 82,9 million followers on his official Twitter account, @realDonaldTrump. Twitter is a popular social media and microblogging service with the number of users increased rapidly over the years. The limitation of 140 letters per tweet results in people having a lower threshold to post opinions, discuss ideas and share impulsive thoughts. Consequently, this makes the platform a good source for collecting and analysing data in terms of clustering, public opinion, human sentiment, social networking patterns and human behaviour (Kwak, Lee, Park, & Moon, 2010; Pak & Paroubek, 2010). Primarily, this study aims to reveal whether

Trump's sentiment and rhetoric impact stock returns. In virtue of being one of the most powerful people in the world (Forbes, 2018), we expect Donald Trump's policies and signals to have a significant influence on individual securities.

Several researchers have already found a significant effect on stock returns which correlates with Trump's tweets (Brans and Scholtens, 2020; Wagner, Zeckhauser and Ziegler, 2018; Juma'h & Alnsour, 2018; Ge, Kurov & Wolfe, 2018; Colonescu, 2018; Born, Myers & Clark, 2017). Brans and Scholtens (2020) evidenced that negative sentiment tweets from the U.S. president, are followed by a market decline for the company mentioned. Wagner et al. (2018) found that relative stock prices adjusted to shifts in expectations regarding Trump's trade policies and tax. High tax firms and companies with significant deferred tax liabilities gained, while companies with deferred tax assets declined. Moreover, their results indicated that domestic-oriented companies performed better than international-oriented companies under Trump's policies. Further, Born et al. (2017) found that positive content tweets elicited positive abnormal returns, while negative content tweets elicited negative abnormal returns for the targeted companies. Ge et al. (2018) presented similar evidence. However, additionally, these researchers found that presidential tweets had an impact on volatility, Bloomberg institutional investor attention and company-specific sentiment. Lastly, Colonescu (2018) found a correlation between various moving average window lengths of tweet content and the Dow Jones Industrial Average (DJIA) index. Additionally, his results indicated some short term and lasting effects on U.S.-Canada and U.S. composite exchange rates. By contrast, Juma'h and Alnsour (2018) found no evidence of influence from presidential tweets on neither market indices nor targeted companies.

These types of anomalies and its causes have also been debated within the field of behavioural finance. Behavioural finance, which concerns the influence of psychology and sociology of investors on financial markets, contradicts much of the efficient markets theory (Shiller, 2004; Fama, 1965). The field has two main building blocks; limits to arbitrage and psychology/investor sentiment. Limits to arbitrage refer to the difficulties for rational investors to undo the dislocations of less rational traders, whereas psychology catalogues deviations from full rationality (Barberis & Thaler, 2003; Shleifer, 2000). Behavioural economists argue that these barriers regularly create mispricing in financial markets. Fischer Black (1986) presented noise traders as one plausible explanation for mispricing in financial markets. Noise traders are unsophisticated investors who trade on noise rather than information, and whose collective shifts of opinion increase the riskiness of returns to assets (De Long, Shleifer, Summers & Waldman, 1990; Black, 1986).

Efficient market theorists argue that such anomalies quickly would be exploited and arbitraged by more sophisticated investors. However, as some researchers have evidenced, this is not always the case. De Long et al. (1990) argues that opinions of noise traders are unpredictable, and arbitrage requires bearing the risk that their misperceptions become even more extreme tomorrow than they are today. Consequently, this creates limitations for arbitrage. De Long et al. (1990) suggest that professional arbitrageurs' behaviour can be seen as a response to noise trading, rather than as trading on fundamentals. This strategy involves detecting signals and patterns that these noise traders follow, in order to bet against them. In such cases, arbitrageurs might actually amplify the effect of feedback traders in anticipation of the price increase they will cause (Shiller, 2004; De Long et al., 1990). Accordingly, Trump's tweets might create noise in financial markets, with some investors misinterpreting it as information and creating anomalies. We discuss this possible explanation based on our observations throughout the study. Another explanation is that Trump tweets are not strictly information-free events. However, if Trump announces new relevant information to the stock market through Twitter, then this is also captured by the abnormal returns in our study.

We conduct our study using the event study methodology, as outlined by A. Craig MacKinlay (1997). To perform the study, we build two portfolios consisting of 24 small-cap companies listed on the S&P 500 index. The first portfolio is value-weighted, and the second is equal-weighted. Each of the 24 companies is, moreover, assessed individually. The tweets' sentiment is classified using consistent criteria and collected from Twitter using relevant keywords. We then treat the included tweets as exogenous macroeconomic events in the study. We employ Fama and French's (2015) five-factor model as our expected (normal) return model. Hence, our research design is clear and well-specified with the defined assumptions necessary to accurately capture the impact of Donald Trump's tweets on small-cap securities' returns.

We perform several tests to determine whether Trump's tweets and Twitter activity affect financial returns in the U.S. market. These tests indicate that Trump's sentiment has an impact on several securities' asset prices. This effect is, moreover, reflected in the two portfolios. Overall, we find that positive sentiment tweets cause positive abnormal returns, whereas negative sentiment tweets cause negative abnormal returns. Furthermore, our results indicate that Trump's sentiment is more difficult to value at an individual security level. Several securities experience a continued drift in firm equity value after the event, which is considered a violation of the semi-strong form of the efficient market hypothesis (EMH). At the portfolio level, we find that positive Trump sentiment is rapidly incorporated, consistent with the EMH. For negative Trump sentiment, however, the cumulative average abnormal return (CAAR) continues to drift downward after the event. Similarly, this is considered a violation of the EMH. Hence, negative Trump sentiment is seemingly more difficult to value than positive Trump sentiment. We check the robustness of our findings by removing outliers and repeating the tests. The outlier removal has limited impact on the significance of our results, and we consider our findings robust.

Besides, we include a secondary study regarding Trump's tweet frequency. In this study, we examine whether a high Twitter activity, as measured by the number of tweets and retweets in a day, cause abnormal returns. We find that the market responds negatively to increased Trump Twitter activity and that the effect persists after multiple days. This prolonged effect is a violation of the EMH and indicates that the market finds it difficult to value Trump's high Twitter activity. Furthermore, we perform independent investigations concerning the impact on trading volume, market volatility and effect over time. We find that trading volume slightly increases for positive tweets and slightly decreases for negative tweets. We discuss this asymmetric relationship in the light of relevant theory. We measure changes in volatility by tracking the Chicago Board Options Exchange Volatility Index (CBOE VIX). We find that volatility increases for negative tweets and decreases for positive tweets. Regarding variability in effect over time, we observe a positive “pull” in Trump’s first period as president. By contrast, there is a negative pull toward the end of 2019. We deliver our thoughts on these results in light of the escalation of the trade war between the U.S. and China, as well as a gradual shift toward Trump announcing more concrete actions on Twitter. However, we can not draw any inferences about the above relationships without thorough statistical evidence and testing.

Our study contributes to the literature in several ways. Firstly, prior research concerning Trump’s tweets effect on stock returns mainly examine whether firm-specific tweets (i.e. where Donald Trump has specifically included or directed a tweet-message to the firm investigated) affect the firm’s equity value. We, therefore, contribute to the literature by measuring whether Donald Trump’s macroeconomic tweets affect financial returns in the U.S. stock market. Moreover, as this study concentrates on small-cap securities, we provide valuable insight into how Trump affect the smaller companies on the S&P 500. Secondly, we contribute to the strand in the literature concerning the predictive value of Twitter. By examining Trump’s social media activity, we contribute to a deepened understanding of the relationship between non-financial information or other indicators on social media, and stock returns. Thirdly, as we employ sentiment analysis in our research, we contribute to revealing further how human emotion or opinion impacts stock returns. Moreover, we discuss our observations relative to social networks and new digital risks for companies. Central actors in the social network, have the power to influence big masses. In turn, these individuals can severely impact firm equity value both negatively and positively. This concept, which we decide to refer to as “opinion leader risk”, is presented and discussed. Fourthly, we provide observations and reflections concerning our results, including possible explanations and causes of the anomalies. These include the potential presence of noise trading, overconfident investors, and the relevance of the information in Donald Trump's tweets for the stock market. Lastly, this study exemplifies how one could deal with total clustering in event studies (MacKinlay, 1997). Total clustering relates to an implication when performing event-studies concerning overlap in calendar time across securities. We explain this issue thoroughly later in the paper.

We organise this paper as follows: The next section presents the theoretical background and related literature to our study. Section 3 describes the data, the process of collecting securities, and the classification of tweets. In section 4, we outline the event study methodology and our use of the Fama and French five-factor model to estimate normal performance. Section 5 presents the empirical results of Trump's effect on financial returns and how long the effect persists. Additionally, we discuss several complementary findings regarding trading volume, volatility and effect variability. Section 6 presents our secondary study regarding tweet frequency. In section 7, we assess the robustness of our results. Section 8 provides a discussion of our analysis and findings. The last section comprises the main conclusions, implications and suggestions for future research.

2 Literature review

2.1 Efficient market theory and the semi-strong form

The semi-strong form of the efficient market hypothesis (EMH) (Fama, 1970; Fama, Fisher, Jensen & Roll, 1969) is concerned with whether security prices at any point in time "fully reflect" all available information. This form of the EMH assumes that when rational investors' expectations toward future cash flow change, the value of the individual security will change accordingly. The theory remains one of the most influential and debated concepts in modern finance, and perhaps the strongest contradictory argument against active investors aiming to beat the market.

Eugene Fama (1970) addresses the efficient market and its consistency with the "fair game" model. He states that there is not much evidence against the notion that security movements develop as a "random walk" (Fama, 1970; Fama, 1965). Implicitly, Fama argues that one cannot predict the market better than the results one could obtain by chance and consequently that one can not consistently gain excess returns. Although he agrees that there might be consistent evidence of dependencies between successive price changes on a day-to-day basis, he argues that there is not much evidence concerning more than one day. Further, Fama admits that there might be some daily trading strategies that would outperform the simpler buy-and-hold investment strategy, but claim that even small brokerage fees would quickly erode these returns. Secondly, he acknowledges that on days with large security movements, the subsequent days usually follow by large movements. Fama explains this phenomenon simply; that it takes some time for investors to evaluate the new information accurately. Lastly, he admits that it might exist overreactions and under reactions in the market, but that these anomalies would occur as frequently as the other, which is considered consistent with market efficiency.

Burton B. Malkiel, another prominent economist, supports and shares Fama's notion of stock price movements as a random walk. Malkiel (2003) published a paper where he dealt with the most frequent and prominent critics against the EMH. He discusses the apparent inefficiencies of markets, predictable patterns of both technical or fundamental nature, and bubbles. However, Malkiel firmly remains with his beliefs and convictions concerning the many associated concepts of efficient or equilibrium markets. He admits that markets are not always entirely rational and that the collective judgment of investors will sometimes make mistakes. Nevertheless, Malkiel (2003) argues that anomalies and phenomenons such as bubbles are exceptions rather than the rule. Moreover, he claims that if such anomalies or inefficient patterns should occur, they will not be around for long.

Even though the EMH is and historically has been subject to much debate, even the most prominent critics do not reject the hypothesis in its entirety. In the next section, we will present some of the main criticisms of the EMH.

2.2 Criticism of the efficient market hypothesis

The efficient market theory has been regularly challenged both theoretically and empirically since the 1980s. Critics of the EMH claim that markets are mostly inefficient, but that efficient or equilibrium markets are extreme states which might occur at times. Paul A. Samuelson's dictum accurately captures this notion by claiming that "markets are micro efficient and macro inefficient" (Fuhrer & Schuh, 1998). Michael C. Jensen (1978) presented some early criticism in the period before and around 1978. This paper included Ball (1978) and Watts (1978), who found that the effect of earnings announcements on security prices was not incorporated as rapidly and correctly as one would expect under market efficiency. Chiras and Manaster (1978) utilised the Black-Scholes-Merton option pricing model to calculate implied variances of future stock returns. The researchers evidenced that in the period between 1973 and 1975, their trading strategy would generate excess returns, and argued thus that the CBOE options market was inefficient. In the subsequent years, Grossman and Stiglitz (1980) further investigated some of the anomalies which contradict the EMH. These researchers did acknowledge the existence of efficient markets and admitted that if the information is very inexpensive, or if investors have very accurate information, equilibrium markets could occur. Moreover, they explained that the market would then eventually reveal these informed traders' information and the anomalies, as a result, would disappear. However, Grossman and Stiglitz (1980) also argue that such markets or equilibriums are rare or unusual, as most of the traders' beliefs and perceptions are homogenous.

Another explanation of the anomalies and excess volatility in the financial markets is the risk of less than rational or noise traders (De Long et al., 1990; Black, 1986). Within the boundaries of finance, Black (1986) defines noise as the contrast to information. Black (1986) argues that such unsophisticated investors, whose opinions and behaviours were highly unpredictable, significantly reduced the attractiveness of arbitrage. Noise investors trade on noise, believing it to be information. Consequently, “the unpredictability of noise traders' beliefs created a risk in the price of the asset that deters rational arbitrageurs from aggressively betting against them” (De Long et al., 1990). Hence, noise trading can cause a substantial divergence between market prices and fundamental values, even in the absence of fundamental risk. However, Black (1986) claims that noise traders are essential for the liquidity and financial markets to work. Moreover, De Long et al. (1990) argue that over the long-run, contrarian or similar fundamental strategies which bets against noise traders, generate excess returns. This is due to the mean reversal in investor sentiment. Contrarian strategies require market timing by investing when noise traders’ sentiment is overly bearish, in anticipation that the sentiment will eventually recover (De Long et al., 1990). In sum, Black (1986) concludes that noise causes markets to be somewhat inefficient, but that it simultaneously often prevents us from taking advantage of these inefficiencies.

Fama frequently disarms evidence against market efficiency as within the boundaries of expected chance deviations (Fama, 1998). Daniel, Hirshleifer and Subrahmanyam (1998) disagree with this viewpoint, as many anomaly return patterns can be both strong and regular. The researchers propose two psychological biases as reasons for market anomalies. These are investor overconfidence about the precision of private information and biased self-attribution. The theory implies that investors overreact to private information signals and underreact to public information signals. Moreover, the researchers show that positive return autocorrelations or patterns can be a result of continuing overreaction. Daniel et al. (1998), draws parallels to the examples of Ball (1978) and Watts (1978), and explain that post-earnings announcement drift may be a continuing overreaction triggered by the earnings announcement to pre-event information. Further, Daniel et al. (1998) clarify that their paper does not concern noise traders (De Long et al., 1990; Shiller, 2004) and trading which is unrelated to valid information, although they address many of the same implications. They investigated whether investors misinterpreted genuine information by endogenously generating trading mistakes that correlated with fundamentals. Daniel et al. (1998) refer to this group and concept as quasi-rational traders. In short, the researchers argue that overconfidence might be a root cause of market inefficiencies and that successful investments might generate more overconfidence. Lastly, Daniel et al. (1998) suggest that such anomalies are most common for small illiquid stocks, as the illiquidity cause barriers for arbitrageurs to exploit the mispricing effectively.

More recent critics, such as Shleifer (2000) and Shiller (2004) build on the strand in the literature concerning behavioural finance in their scepticism toward the notion of market efficiency. Shleifer (2000) builds on the work from Black (1986) and Daniel et al. (1998). For instance, Shleifer (2000) provides evidence that in anticipation of noise traders, arbitrageurs sometimes move prices further away from fundamental values instead of toward it, as one would expect under the EMH. Shiller (2004), moreover, argues that the fundamental value of stocks is hard to measure. He insists that we distance ourselves from the presumption that financial markets always work well and that price changes always reflect genuine information. Further, he argues that some patterns last longer than what is accepted within the boundaries of efficient market chance deviations. If speculative bubbles last for a long time, the relation to fundamental values may not be observed except in very long sample periods (Shiller, 2004). He claims that significant market events usually occur due to similar thinking between a large group of people and that news media are the vehicles that spread the ideas (Shiller, 2000). Both Shleifer and Shiller address and provide evidence for the two main explanatory variables of inefficiencies in behavioural finance, limits to arbitrage and investor sentiment.

As documented in the section above, there exist significant but somewhat fractionated evidence against the EMH. However, many of the pillar stones which the EMH builds upon, remain steadfast and firm. There is broad acceptance toward the notion that security prices react to new and unexpected news, that there is a strong relationship between fundamentals and stock price movements, and over a long horizon the correct or “fair” value of a stock will occur at times. Nonetheless, several challenges have been raised regarding the efficiency and rationality of the market and its participants. Similarly, in this study, we will discuss our findings in the light of the EMH, and comment on whether they are considered consistent with Fama's evidence.

2.3 Twitter as a predictive tool for forecasting future outcomes

Over the last decades, there have been conducted several studies on the explicit effect or predictive value of different social media. An early study by Asur and Huberman (2010), measured the predictability of chatter from Twitter by forecasting box-office revenues for movies in advance of their release. The researchers found that there was evidence suggesting that increased attention concerning a movie had a positive correlation with later rankings. Dhar and Chang (2009) found similar evidence when conducting a study on how the volume of blog posts about an album positively correlated with future sales. These studies helped to sow the seeds for modern analysis of social media and its relevance and application for the business world.

Later, Wang, Can, Kazemzadeh, Bar and Narayanan (2012) used real-time Twitter sentiment analysis to investigate if one could predict the 2012 U.S. Presidential Election. These researchers built a system which captured the public sentiment and opinion toward the different candidates. The system allowed them to track how public sentiment shifted in the wake of different political news or events. The study contributed to the field by exemplifying how one could instantly and continuously track public response to political messages and events. In the same manner, Luo et al. (2013) investigated the predictive relationship between public indicators on social media and firm equity value. These researchers found that social media metrics, such as web blogs or consumer ratings, were significant indicators of firm value. Conventional online behaviour-metrics was also found to have a significant predictive ability on firm value, but these findings were substantially weaker than social media metrics. Additionally, Luo et al. (2013) discovered that social media had more rapid predictive value than conventional online media activity.

A more recent study by Bartov, Faurel and Mohanram (2018) investigated whether aggregated individual tweets could predict earnings announcements and stock returns. The results held for tweets that conveyed original information, as well as tweets that disseminated existing information. However, the effect was more substantial for tweets providing information directly related to firm fundamentals and stock trading.

As all these studies show, there might exist indicators in the public activity and wisdom of crowds on social media, which in turn can help forecast or predict future outcomes. Moreover, Twitter represents a highly dynamic and complex knowledge base, which often can outpace other media in terms of breaking news, trends or sentiment (Kwak et al., 2010).

2.4 Twitter sentiment impact on stock returns

Public sentiment and its potential spillover effects have become subject to much scrutiny in the later years. Although several of the papers mentioned above include elements of sentiment analysis (e.g. Asur and Huberman, 2010; Wang et al., 2012), this section will focus exclusively on the effect of public sentiment (broadly defined) on stock returns.

Baker and Wurgler (2006) provide some early insight into the effect of sentiment on stock returns. Their findings challenge much of the classical finance theory. These researchers found that investor sentiment has greater effects on securities whose valuations are highly subjective and difficult to arbitrage. When beginning-of-period proxies for the sentiment were low, small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks tended to earn subsequent high returns. However, when beginning-of-period proxies were high, the same stocks seem to earn subsequent low returns. Furthermore, Baker and Wurgler (2006) conclude that large firms are less sensitive to sentiment than the abovementioned stocks.

Another prominent study by Bollen et al. (2010) investigated how Twitter mood might help predict stock market returns. They utilised two sets of algorithms to classify and analyse people's sentiment on Twitter feeds. The algorithms used were OpinionFinder and their own-developed algorithm Google Profile of Mood States (GPOMS), which measured moods in terms of six dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). After they had successfully classified the public sentiment, the researchers tested whether there was a correlation or predictive value between the public moods and the returns of the Dow Jones Industrial Average (DJIA). The researchers found that specific dimensions had a strong predictive value, while others did not. Notably, the calm mood-dimension seemed to have a strong predictive value on the DJIA, providing similar price movements after 3 or 4 days. Likewise, Zhang, Fuehres and Gloor (2011) measured daily collective hope and fear and analysed the correlation between different indices and stock market indicators. Moreover, the authors found that emotional tweet percentage significantly correlated negatively with Dow Jones, NASDAQ and S&P 500, while displaying significant positive correlation to VIX. Zhang et al. (2011) conclude that emotional outbursts on Twitter are a good predictor of how the stock market will be doing the next day.

Yu, Duan, and Cao (2013) assessed the effect of social and conventional media on short term stock performance. The social media analysis included blogs, forums, and Twitter. The conventional media analysis included major newspapers, television broadcasting companies, and business magazines. These researchers' findings suggest that overall social media has a stronger relationship with firm stock performance than conventional media. Similar evidence was found in a paper by Ranco, Aleksovski, Caldarelli, Grčar and Mozetič (2015), concerning the impact of public sentiment on the companies that form the Dow Jones Industrial Average (DJIA) index. These researchers found significant evidence of dependency between firm-specific Twitter-sentiment and the individual stocks' returns. Moreover, they argued that Twitter-sentiment predicted the direction of market evolution for individual stocks.

Interestingly, as a side note, Edmans, Garcia and Norli (2007) even found that sports results had a significant effect on financial returns. These researchers tested whether soccer affected stock returns. Edmans et al. (2007) found a significant market decline after soccer losses on the losing nation's stock returns. Moreover, the loss effect was more influential in small stocks and after more important games. Additionally, the researchers also document effects for basketball, cricket or rugby games. This research gives an interesting example of the interdependencies in human sentiment, and how a seemingly unrelated event might impact stock returns.

In sum, the research listed above implies that investor sentiment might have a significant impact on stock returns. Moreover, investor sentiment obtained from social media might contain predictive signals for future outcomes.

2.5 Trump's tweets impact on stock returns

In the later years, President Trump's impact on global financial markets has received increased interest. Wagner et al. (2018) investigated the short- and long-term effect of Donald Trump's surprise election. The researchers found that relative stock prices adjusted appropriately and in line with the shift in expectations regarding Trump's trade policies and tax. High tax firms and companies with significant deferred tax liabilities gained, while companies with deferred tax assets declined. Secondly, domestic-oriented companies fared better than internationally oriented companies. Moreover, Wagner et al. (2018) evidenced that consequences regarding deferred tax liabilities, deferred tax assets were rapidly incorporated, whereas more complex issues such as net deferred tax liabilities and foreign exposure were more challenging to value. Lastly, this study also provides documentation that expectations concerning tax rates, impact firm valuations.

Both Born et al. (2017) and Ge et al. (2018) analysed the effect of Trump's tweets which aimed at specific publicly traded companies. Born et al. (2017) found evidence suggesting that positive content tweets elicited positive abnormal returns, while negative content tweets elicited negative abnormal returns for the targeted companies. Based on the price response, and the increase of trading volume and google activity, the researchers suggest that noise traders are the primary cause of abnormal returns. However, as the researchers found that the CARs were insignificant after five trading days, they conclude that the effect of these noise traders was transitory. Ge et al. (2018) presented similar evidence that firm-specific tweets moved stock market prices and increased volume traded. However, additionally, these researchers found that presidential tweets had an impact on volatility, Bloomberg institutional investor attention and company-specific sentiment. This effect was comparatively stronger after Trump's inauguration. Perhaps the most recent contribution to this topic is Brans and Scholtens (2020). The authors evidenced that tweets from Trump, which revealed strong negative sentiment, were followed by a market decline for the company mentioned. On the other hand, supportive tweets did not render any significant effects.

Another researcher, Colonescu (2018), investigated whether Donald Trump's daily tweet flow affected U.S. financial and foreign exchange markets. By employing text mining techniques, he found a correlation between various moving average window lengths of tweet content and the Dow Jones Industrial Average (DJIA) index. Additionally, Colonescu (2018) found some short term and lasting effects on U.S.-Canada and U.S. composite exchange rates. By contrast, Juma'h and Alnsour (2018) found no evidence of influence from Trump's tweets on neither market indices nor targeted companies. Based on the results, the researchers argued that either the tweets only influenced the companies share prices in a spontaneous moment or the information contained in Trump's tweets was already reflected in the share prices before the day it was published. In conclusion, their findings indicated that Trump's tweets had no impact on financial returns, consistent with the efficient market assumptions.

Most of the studies presented above concern Trump's firm-specific tweets. Less attention has been paid to Trump's tweets of macroeconomic nature. Although most researchers agree that Trump's tweets do indeed affect various financial returns, Juma'h and Alnsour (2018) provide exciting counterarguments and contradicting evidence. In sum, these papers present important findings and reflections, which provide the backdrop of our study. In the next section, we will present our data, as well as describe the process of classifying sentiment and collecting relevant tweets.

3 Data

3.1 Data collection

We extracted the data from Twitter, using the advanced search function, and a third-party site, Trump Twitter Archive, which is a dedicated network for Trump's tweets. We downloaded a total of 21900 tweets from the period June 2015 to December 2019. However, we set the period of investigation to 08.11.2016, when Trump won the election, through 31.12.2019. After the tweets were extracted, we used R/R-studio, ExCel and Stata to clean the data, perform statistical analyses and regressions. We extracted the financial data for each security using daily adjusted closing prices from Yahoo! Finance and included data from January 2012 through 2019. When company stocks were split into different classes of shares (e.g. based on their respective level of voting rights), we consistently chose the A-class shares. We extracted Fama and French's five-factor model data from Kenneth R. French's website. The portfolios in French's data are constructed using American NYSE and Nasdaq firms, which makes these factors both comparable and precise as a basis for normal return calculation in our study. The raw financial data of each firm was modified into arithmetic returns to be compatible with the five-factor data, as well as to aggregate and create unbiased portfolios. In total, this study consists of 40 selected tweets (20 positive and 20 negative tweets). These tweets were manually identified, classified and extracted from Donald Trump's official Twitter account @realDonaldTrump. Moreover, the tweets have been collected evenly throughout the period and cover a large proportion of Trump's term as president.

3.2 Security selection

The companies and the portfolio included in the study consist of 24 small-cap firms in the S&P 500. Since our period of interest includes financial returns from 2016 (when Trump got elected as president) through 2019, we used the market cap from the beginning of the period. Hence, we conducted the study as if the portfolio was constructed at the start of 2016. The included sample securities had to be sufficiently traded, as thinly traded securities might cause biases in the estimated variables when performing the OLS regression (Scholes & Williams, 1977). Moreover, this help avoids liquidity bias in asset pricing. Poor liquidity could potentially harm the accuracy of our study and create an upward bias (Asparouhova, Bessembinder & Kalcheva, 2009). Accordingly, by excluding illiquid securities, we sufficiently reduce such upward bias. The companies included in the study are listed in Table 1 below:

Table 1: Company overview

Ticker	**Company name**	**Industry**	**Market Cap (USD)**
AAL	American Airlines Group Inc.	Airlines	16 533 M
UAL	United Airlines Holdings Inc.	Airlines	16 151 M
NWL	Newell Brands Inc.	Household & Personal Products	15 927 M
APA	Apache Corp.	Oil & Gas E&P	15 013 M
NBL	Noble Energy Inc.	Oil & Gas E&P	14 993 M
NLSN	Nielsen Holdings Plc.	Consulting Services	13 736 M
NOV	National Oilwell Varco Inc.	Oil & Gas Equipment & Services	12 866 M
ADS	Alliance Data Systems Corp.	Credit Services	12 352 M
MOS	The Mosaic Company	Agricultural Inputs	9 942 M
KIM	Kimco Realty Corp.	REIT—Retail	8 534 M
BWA	BorgWarner Inc.	Auto Parts	8 189 M
GPS	The GAP Inc.	Apparel Retail	7 736 M
DXC	DXC Technology Company	Information Technology Services	6 460 M
SEE	Sealed Air Corp.	Packaging & Containers	6 286 M
HOG	Harley-Davidson Inc.	Recreational Vehicles	6 014 M
UNM	Unum Group	Insurance—Life	5 861 M
PBCT	People's United Financial Inc.	Banks—Regional	5 535 M
FLS	Flowserve Corp.	Specialty Industrial Machinery	5 070 M
XRX	Xerox Holdings Corp.	Information Technology Services	4 976 M
RL	Ralph Lauren Corp.	Apparel Manufacturing	4 936 M
RHI	Robert Half International Inc.	Staffing & Employment Services	4 850 M
IPGP	IPG Photonics Corp.	Semiconductor Equipment & Materials	4 552 M
HP	Helmerich & Payne Inc.	Oil & Gas Drilling	4 408 M
PWR	Quanta Services Inc.	Engineering & Construction	2 775 M

This table provides an overview of the included securities in the study. We also aggregated the securities into portfolios which are investigated separately in this paper. The first column shows each respective security's ticker code. In the second column, we present the individual securities by their official name. The third column shows which industry the security belongs to, as categorised by Yahoo! Finance. Finally, in the last column, the market cap for individual securities is presented.

3.3 Tweet sentiment classification and selection

The tweets have been manually classified as either positive or negative using consistent criteria, and the assistance of SentiStrength (n.d.). SentiStrength is an automated sentiment classifier, developed as part of the CyberEmotions project, funded by the EU (FP7) (SentiStrength, n.d.). Positive tweets have been selected based on three aspects. The tweet must have had important positive macroeconomic news value to the stock market, positive overall signal effect or a predominance of positively charged words such as “progress”, “strong”, “happy”. Likewise, negative tweets must have had important negative macroeconomic news value to the stock market, negative overall signal effect, or a predominance of negatively charged words such as “difficult”, “disgrace”, “bad”. Often Trump posts multiple tweets concerning the same topic. In such cases, the first tweet serves as a representative for that whole series of tweets. We identified the tweets using the advanced search function in Twitter and keywords such as “Tariff”, “China”, “Fed”, “Russia”, “Tax” or “Deal”.

4 Research methodology

4.1 Procedure for an event study

To measure the impact of U.S. President Donald Trump’s on financial securities’ returns, we employ a conventional event study methodology, as outlined by MacKinlay (1997). Event studies provide a systematic procedure for measuring the impact of a business event or announcement on the firm value (shareholder value) (Godfrey, Merrill & Hansen, 2009). The event study has many applications from both firm-specific to economy-wide events. The cleanest evidence on market-efficiency comes from event studies on daily returns. Moreover, event studies can illustrate how rapidly prices adjust to new information (Fama, 1991). In this study, we define Trump’s tweets concerning macroeconomic issues as our events of interest.

To examine the impact of Trump's tweets, we measure if the events cause any abnormal returns. Abnormal returns are calculated by deducting the normal returns from the actual returns of the firms or portfolios. The normal return is defined as the expected return without conditioning on the event taking place (MacKinlay, 1997). This follows from the simple formula below (for firm or portfolio *i* at event date *t*):

$$AR_{it} = R_{it} - E(R_{it}|X_t) \tag{1}$$

where:

AR_{it} : Abnormal return.

R_{it} : Actual return.

$E(R_{it}|X_t)$: Expected normal return.

4.1.1 Event window

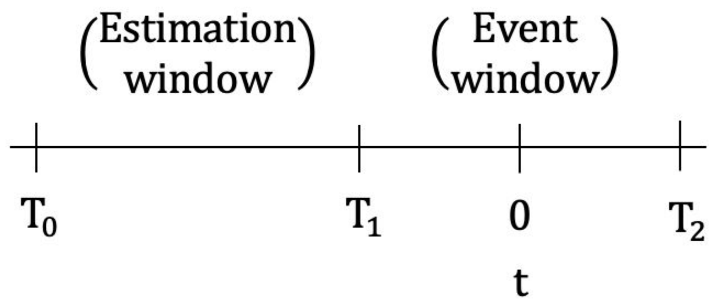
We set the event window to five days before and after the event (-5,5). Each event date relates to a specific tweet investigated. $t = 0$ illustrates this specific date. We choose to expand the event window, to check whether the market acquires information before the actual announcement or forecast the event happening in advance. Such pre-event effects are referred to as leakage and might make it difficult to determine when the event actually happens. By including a period before and after the event, one account for such event date uncertainty (MacKinlay, 1997). Initially, we set our event window to ± 15 days, but due to short periods between some events, we choose to reduce the event window interval.

4.1.2 Estimation window and sampling interval

The estimation window is set to 1005 days before the first event, using daily data as our sampling interval (i.e. all open trading days between 01.01.2012 and 31.12.2015). In this study, we apply a single estimation window due to insufficient time in-between events. The role of the estimation window is to provide a representative and unaffected relationship between the security of interest and the normal performance model. As our estimation window is sufficiently large, we consider this requirement fulfilled. This relationship will later be used as a proxy for normal return in the event window to calculate abnormal returns.

Formally, the two windows presented above are specified as follows:

Figure 1: Event study timeline



$t = 0$ illustrates the date of the event. $t = T_0 + 1 + ... + T_1$ represents the estimation window and $t = T_1 + 1 + ... + T_2$ illustrates the event window. Further, let $L_1 = T_1 - T_0$ be the estimation window and $L_2 = T_2 - T_1$ be the event window (MacKinlay, 1997).

4.2 Model for measuring normal performance

4.2.1 Five-factor model

In this study, we apply the influential five-factor asset pricing model by Fama and French (2015) as a measure of normal stock performance, i.e. as if the event would not occur. The five-factor model is a multifactor model which builds on the original Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965). The CAPM is a common model used in several previous event studies (MacKinlay, 1997). In their 1993 paper, Fama and French expanded the CAPM model by adding two additional variables, firm size and book-to-market equity (Fama & French, 1993). However, as there was still some return variance left unexplained by the three-factor model, they further expanded the model by adding two additional factors, profitability and investment (Fama & French, 2015). In sum, the five-factor model is a comprehensive model used to measure the relationship between average returns and different risk factors or premiums.

We conducted our original study using the market model on a sample of the 15 largest firms of the S&P 500. The market model is an example of a one-factor model. The main benefits of using this model are that it removes the variance in the abnormal return, which is related to the variance in the market return. This variance reduction depends on the R^2. The higher the R^2, the larger is the gain (MacKinlay, 1997). However, as our hypothesis builds on the assumption that Trump's macroeconomic tweets affect the market as a whole (including the reference index), we find the market model inapplicable for our analysis.

Similarly, as above, the benefits of using a multifactor model increases with the reduction in variance in the abnormal return by explaining more of the variance in the normal return. Such abnormal variance reduction is greatest when the sample securities have some common characteristic, e.g. in terms of size or industry (MacKinlay, 1997). Accordingly, we collect the sample firms in our study from the same market capitalisation group (bottom 60 of the S&P 500).

We apply the following five-factor model (for security or portfolio *i* for period *t*):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \tag{2}$$

where:

R_{it} : Return on stock or portfolio

R_{Ft} : Risk-free rate

$R_{it} - R_{Ft}$: Excess return

R_{Mt} : Return on the value-weight market portfolio

$R_{Mt} - R_{Ft}$: Market risk premium

SMB_t : Return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks

HML_t : The difference between the returns on diversified portfolios of high and low B/M stocks

RMW_t : The difference between the returns on diversified portfolios of stocks with robust and weak profitability

CMA_t : The difference between the returns on diversified portfolios of the stocks of low (conservative) and high (aggressive) investment firms

e_{it} : Zero-mean residual

a_i : Intercept

b_i , s_i , h_i , r_i and c_i : Estimated factor coefficients

(Fama & French, 2015)

4.3 Measuring and analysing abnormal returns

4.3.1 Estimation of the expected (normal) return using the five-factor model

We calculate the expected return using an OLS regression between the individual stocks or portfolio and the five-factor model data over the estimation window period (N=1005). Hence, we estimate the intercept a_i and each of the slope coefficients b_i , s_i , h_i , r_i and c_i for the five individual factors in the model from equation (2).

4.3.2 Statistical properties of abnormal returns

Given the five-factor model parameter estimates from the section above, one can measure and analyse the abnormal returns to observe how the actual return differs from the expected return. Correspondingly, using the five-factor model to calculate the normal return, the abnormal return for security or portfolio *i* in the event window, can be calculated as follows:

$$AR_{it} = R_{it} - R_{Ft} - (a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t) \tag{3}$$

where the abnormal return is the error term of the five-factor model calculated on an out of sample basis.

The conditional variance is divided into two parts, the variance from the error term in equation (2) and additional variance due to the sampling error in the estimated factor parameters. However, as the estimation window becomes sufficiently large, the sampling error of the parameters will approach zero.

Similarly, one can assume that the contribution of the second part to the variance of the abnormal returns is zero. Hence, we get that:

$$\sigma^2(AR_{it}) = \sigma^2_{\varepsilon_i} \tag{4}$$

The abnormal returns will follow a normal distribution under the null hypothesis, which states that the event does not have any impact on the returns:

$$AR_{it} \sim N(0, \sigma^2(AR_{it})) \tag{5}$$

4.3.3 Aggregation of abnormal returns

Next, to successfully conduct our study across multiple events, the abnormal return observations must be aggregated. When aggregating across events, there are several possible biases and obstacles that one must take into consideration. One such implication is clustering (MacKinlay, 1997). The aggregated abnormal return model assumes that the event windows do not overlap across securities. This assumption allows for calculating the variance of sample cumulative abnormal returns without concern about the covariance across securities since they are zero (MacKinlay, 1997). However, when they do overlap, the distributional results for the aggregated abnormal returns are no longer applicable. There are two solutions to this issue; 1) One can aggregate the abnormal returns into a portfolio dated using event time, and the security level analysis (presented later in this section) can be applied to the whole portfolio. Alternatively, 2) one can analyse the abnormal returns without aggregation. Hence, this implies testing the null hypothesis of the event having no impact using unaggregated security by security data. This approach is most commonly used when there is an event on the same day for several firms (MacKinlay, 1997).

As our study has total clustering, meaning all events included in our study overlap in calendar time across securities, we decide to both run a hypothesis test for unaggregated securities, as well as for all the same securities built as portfolios. Hence, in this study, we aggregate across time (events), but *not* across securities. We include two portfolios in our study. The first portfolio is value-weighted by each security's market capitalisation at the beginning of 2016. The second portfolio is equal-weighted as if one had invested an equal share into each security at the beginning of 2016. Baker and Wurgler (2006) state that large firms will be less affected by sentiment and argue that value-weighting will tend to obscure relevant patterns. Thus, by adding an equal-weight portfolio, we account for such potential bias. Further, the advantage of using unaggregated security by security analysis is that it allows for conducting independent abnormal return-analysis for each security. In turn, this makes it possible for us to measure which stocks have a negative impact or positive impact from Trump's tweets.

However, the unaggregated securities method has two drawbacks. The test statistics might have poor finite sample properties, and the test might have little statistical power. In turn, this test power bias increases the probabilities of performing type 2 errors, i.e. failing to detect or verify abnormal returns and thus failing to reject the null hypothesis. However, when statistical significance becomes harder to obtain, statistically significant results become increasingly reliable. Additionally, by applying the five-factor model, which is considered a stricter model relative to other models, as well as including a parallel analysis of the stocks as portfolios, we increase the overall robustness and value of our study.

Next follows a step-by-step calculation of the aggregated cumulative abnormal return model.

The cumulative abnormal return (from t_1 to t_2 where $T_1 < t_1 \leq t_2 \leq T_2$) is derived from the simple formula (for security or portfolio *i*):

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \tag{6}$$

As the estimation window becomes sufficiently large, the variance of CAR_i is:

$$\sigma_i^2(t_1, t_2) = (t_2 - t_1 + 1)\sigma_{\varepsilon_i}^2 \tag{7}$$

Whereas the distribution of the cumulative abnormal return under the null hypothesis is:

$$CAR_i(t_1, t_2) \sim N(0, \sigma^2(t_1, t_2)) \tag{8}$$

To test the null hypothesis, we aggregate the observations of the abnormal return using AR_{it} from equation (3). In this study, given N events (tweets) for period $t = T_1 + 1 + ... + T_2$, the average abnormal return (AAR) is:

$$AAR_{it} = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{9}$$

Given a sufficiently large estimation window, the variance for the individual security or portfolio i is:

$$var(AAR_{it}) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma^2_{\varepsilon_i} \tag{10}$$

In this study, for any interval within the event window, the cumulative average abnormal return (CAAR) for the individual security or portfolio i is defined as:

$$CAAR_i(t_{1,} t_2) = \sum_{t=t_1}^{t_2} AAR_{it} \tag{11}$$

$$var(CAAR_i(t_1, t_2)) = (1/N^2) \sum_{i=1}^{N} (t_2 - t_1 + 1)\, \sigma^2_{\varepsilon_i} \tag{12}$$

Where N is the total number of events. To test for the null hypothesis, that the abnormal returns are zero, we assume that:

$$CAAR_i(t_1, t_2) \sim N\left[0, var(CAAR_i(t_1, t_2))\right] \tag{13}$$

4.4 Hypotheses and significance testing

Eventually, to test the hypothesis of whether President Trump's tweets impact the financial returns of the included securities or portfolios, we use the following test statistic:

$$t_{CAAR} = \frac{CAAR_i(t_1,t_2)}{var(CAAR_i(t_1,t_2))^{1/2}} \sim N(0, 1) \tag{14}$$

Based on the fundamental view of efficient markets, that security prices fully reflect all available information; we formally test the following hypothesis to assess whether President Trump influences financial returns and how long these potential anomalies last:

$$H_0 : CAAR_i = 0$$
$$H_A : CAAR_i \neq 0$$

for each security or portfolio *i*.

If the cumulative average abnormal returns are significantly different from zero, we reject the null hypothesis that Donald Trump does not have an impact on financial returns. Secondly, if the cumulative average abnormal returns continue to drift, it will be considered a violation of the semi-strong form of the efficient market hypothesis.

5 Empirical results

In this section, we start by presenting the regression results, which constitute our normal performance models. Secondly, we show the results for the abnormal return aggregations across events for each firm or portfolio. Thirdly, we present an in-depth analysis of the cumulative average abnormal return for positive and negative tweets. In this part, we also present the statistical significance of our results.

5.1 Fama and French five-factor model coefficients

Table 2 describes the Fama and French five-factor regression results. We calculate the sensitivities using an OLS regression between the individual security or portfolio and the five-factor model data over 1005 days prior to the first event date (i.e. across all open trading days between 01.01.2012 and 31.12.2015). Each coefficient indicates the respective security or portfolio’s sensitivity toward the different risk factors.

Table 2: Five-factor regressions results per company or portfolio

Company	Intercept	Mkt-RF	SMB	HML	RMW	CMA	R^2
American Airlines Group Inc.	0,002	1,231	0,134	−0,999	−0,655	1,571	0,148
United Airlines Holdings Inc.	0,001	1,071	0,123	−1,097	−1,120	1,512	0,161
Newell Brands Inc.	0,001	1,110	0,039	−0,324	0,157	0,757	0,419
Apache Corp.	−0,001	1,175	−0,001	1,459	0,089	−0,816	0,350
Noble Energy Inc.	−0,001	1,328	0,302	1,274	0,272	−0,838	0,412
Nielsen Holdings Plc.	0,000	0,910	0,014	−0,161	0,173	0,370	0,294
National Oilwell Varco Inc.	−0,001	1,046	0,171	1,287	0,243	−0,876	0,345
Alliance Data Systems Corp.	0,000	1,039	−0,004	−0,471	−0,144	0,418	0,407
The Mosaic Company	−0,001	1,093	0,107	0,533	0,317	0,092	0,283
Kimco Realty Corp.	0,000	0,943	−0,179	−0,249	−0,011	0,709	0,404
BorgWarner Inc.	0,000	1,415	0,456	0,349	0,480	−0,207	0,483
The GAP Inc.	0,000	0,982	0,444	−0,391	0,618	0,771	0,216
DXC Technology Company	0,001	1,130	0,162	0,388	0,176	−0,363	0,272
Sealed Air Corp.	0,000	1,236	0,235	−0,085	0,137	0,506	0,320
Harley-Davidson Inc.	0,000	1,209	0,135	−0,102	0,333	0,266	0,356
Unum Group	0,000	1,097	0,065	0,946	−0,354	−0,323	0,601
People's United Financial Inc.	0,000	0,750	0,220	0,765	−0,153	−0,144	0,505
Flowserve Corp.	0,000	1,272	0,580	0,591	0,454	0,338	0,469
Xerox Holdings Corp.	0,000	1,281	0,180	0,379	0,068	−0,006	0,395
Ralph Lauren Corp.	−0,001	1,090	0,234	0,003	0,580	0,123	0,265
Robert Half International Inc.	0,000	1,253	0,379	−0,112	0,204	0,422	0,459
IPG Photonics Corp.	0,000	1,191	0,541	0,216	−0,162	−0,984	0,251
Helmerich & Payne Inc.	0,000	1,333	0,630	1,981	0,511	−1,239	0,378
Quanta Services Inc.	0,000	1,156	0,611	0,523	0,089	0,438	0,298
Portfolio (VW)	0,000	1,130	0,174	0,186	0,018	0,202	0,818
Portfolio (EW)	0,000	1,139	0,232	0,279	0,096	0,104	0,874

The first column shows which security or portfolio (dependent variable) that is regressed toward the five factors (independent variables). The second column shows the intercept of each regression. In column 3-7, we present each portfolio or security's sensitivity toward the different risk factors. The last column shows each regression model's R-squared.

Since the sensitivities to the five factors $(R_M - R_F)$, SMB, HML, RMW and CMA capture all variation in the expected return, the expected value of the intercept, a_i, is zero for all securities and portfolios *i* (Fama & French, 2015). As the results in Table 2 illustrate, the intercept for each regression model is (very close to) zero. Consequently, the variance of return for the securities or portfolios is primarily explained by their respective sensitivities toward the different factors.

5.2 Testing statistical assumptions

All our data and regression models are thoroughly assessed. To check for *heteroscedasticity*, we first conduct a visual inspection by plotting the residuals against the fitted values of each focal firm or portfolio. Then we perform the Breusch-Pagan / Cook-Weisberg test and White's test for heteroskedasticity. The test statistics implies no presence of heteroscedasticity in the residuals. Thus, the assumption of conditional homoscedasticity is fulfilled. We first assess whether there is a *linear dependence* between the dependent variables (the focal firms or the portfolios) and the independent variables (each of the five factors) by plotting a matrix. This criterion is fulfilled for all variables. *The expected value of the mean of the error term should be zero*. This implies strict exogeneity and ensures that the error term does not influence the estimated coefficients. We predict the residuals for each model and find that all means for the respective residual predictions are close to zero. Hence, this criterion is fulfilled for all variables.

We test for *multicollinearity* using the VIF-test (variance inflation factor) in Stata. Multicollinearity can harm the precision of the estimates and cause bias in our model. We find no presence of multicollinearity between the independent variables. Thus, our estimates are considered reliable and precise. To test whether the *error terms are normally distributed*, we make a kernel density estimate of the residuals and plot a standardised normal probability graph. All residuals follow a normal distribution for all models. To assess the *goodness-of-fit*, we calculate the R^2. The R^2 varies between 14,8-60,1% for all security models. At the portfolio level, the R^2 varies between approximately 81-87%. The R^2 results imply that the independent variables explain 14,8-87% of the variance in the dependent variables for the respective models. As these results indicate, there is a stronger relationship between the dependent variables and independent variables at the portfolio level than at the individual security level. This inference makes sense, as our portfolios are well-diversified across industries and sizes. By nature, the return variance for diversified portfolios is smaller than for single securities.

Hence, after a thorough assessment of all statistical assumptions, we find no critical violations, and we consider our data reliable. We thus proceed to use the regression results in our analysis.

5.3 Average abnormal returns (AAR)

Table 3 describes the average abnormal returns for each respective portfolio on the specified day surrounding the event. The full analysis for each security is found in the appendices. These AAR results are aggregated across 20 events for each specific day in the event window. “Positive” relates to positive tweets, whereas “Negative” concern negative tweets.

Table 3: AAR for portfolios

	Portfolio (VW)		**Portfolio (EW)**	
Day	Positive	Negative	Positive	Negative
−5	0,002	−0,004	0,002	−0,003
−4	0,003	−0,004	0,002	−0,002
−3	0,002	−0,002	0,002	−0,001
−2	0,004	0,000	0,004	−0,001
−1	0,001	−0,003	0,002	−0,003
0	0,000	−0,003	0,000	−0,003
1	−0,001	0,002	−0,001	0,002
2	0,001	−0,001	0,000	−0,001
3	0,000	−0,001	0,000	−0,001
4	0,000	0,000	0,000	0,000
5	−0,001	−0,002	−0,001	−0,001

This table shows the average abnormal returns (AAR) for each day in the event window for the value-weighted and the equal-weighted portfolio. The first column illustrates days in the event window relative to the event date (day 0). The “Positive” columns refer to tweets with positive Trump sentiment, whereas the “Negative” columns refer to tweets with negative Trump sentiment.

As Table 3 shows, there are several occurrences of abnormal returns prior to the events. At the event date, there is zero abnormal return for positive tweets for both portfolios. For negative tweets, there is a negative abnormal return of approximately -0,3% for both portfolios. After the event, some negative effects occur.

5.4 Cumulative average abnormal returns (CAAR)

In this section, we present the cumulative average abnormal return analysis. Below follows the CAAR-table for the two portfolios. The full individual security analysis can be found in Table 8 in the appendices.

Table 4: CAAR for portfolios

	Portfolio (VW)		**Portfolio (EW)**	
Day	Positive	Negative	Positive	Negative
−5	0,002	−0,004	0,002	−0,003
−4	0,005	−0,008	0,004	−0,005
−3	0,007	−0,009	0,006	−0,007
−2	0,011	−0,010	0,010	−0,007
−1	0,013	−0,012	0,011	−0,010
0	0,013	−0,016	0,011	−0,013
1	0,012	−0,014	0,011	−0,011
2	0,013	−0,015	0,011	−0,012
3	0,013	−0,016	0,011	−0,013
4	0,013	−0,016	0,011	−0,013
5	0,012	−0,018	0,011	−0,015

This table shows the cumulative average abnormal returns (CAAR) for the full 11-day period for the value-weighted and the equal-weighted portfolio. The first column illustrates days in the event window relative to the event date (day 0). The "Positive" columns refer to tweets with positive Trump sentiment, whereas the "Negative" columns refer to tweets with negative Trump sentiment.

As can be seen in Table 4, most of the effect seems to occur before the event. Seemingly, there are more fluctuations for negative tweets than positive tweets in the period surrounding and after the event. The effect for positive tweets is gradually incorporated before the event and stable after the event. This indicates close to zero abnormal returns in the period after the event. In the next section, we will test for significance and present a more in-depth analysis of these findings.

5.5 In-depth CAAR-analysis and significance tests

Next, we present an in-depth CAAR-analysis. Note: An important distinction from other event studies is that each CAAR presented in these tables is aggregated across time (events), but *not* across securities. This is due to total clustering, as thoroughly described previously in this paper. Hence, the results are presented for each security or portfolio individually and should be likewise interpreted, separately. Vertically, the tables show CAAR for different event window intervals. The first event window presented, (-5,5), represent the entire window, which is also illustrated in its entirety above. The other windows are smaller intervals either before, during, or after the event. The T-statistic is found on the second line, below each associated CAAR. On the third line, ***, **, and * represent a significance level of 1%, 5%, and 10%, respectively. “Insign.” indicates that the CAAR is insignificant.

5.5.1 Positive Donald Trump Twitter sentiment

We start by presenting the evidence found in Table 10 in the appendices for positive tweets. As the table describes, several securities show significant results for the entire 11-day event window. The portfolios both show significant results at a 1% level for the entire event window. The cumulative average abnormal return of the value-weight portfolio (VW) is 1,2%, whereas the CAAR of the equal-weight portfolio (EW) is 1,1%. These results imply that when Donald Trump tweets a positive tweet concerning macroeconomic issues, the portfolios, which consist of all the 24 sample securities, would cumulatively increase 1,2% and 1,1% across a period of 11 days. Moreover, this indicates that the market values a positive Trump sentiment as correspondingly positive for the overall value of the respective portfolios. However, the CAAR is insignificant for both portfolios in the period surrounding and after the event.

In the individual security analysis for positive tweets, we find that People’s United Financial Inc. and Kimco Realty Corp. are statistically significant at a 5% level, with a cumulative average abnormal return of 1,1% and -1,7% respectively for the full event window. Interestingly, we note that Kimco Realty Corp. has a negative effect from positive sentiment. This implies that when Donald Trump publishes positive tweets, Kimco Realty Corp. experiences a negative impact on firm equity value. Furthermore, Unum Group and Newell Brands Inc. also show significant results at a 10% level for the full event period, with CAAR of 1,1% and 1,7% respectively. Additionally, Unum Group is statistically significant at a 1% level for the (-1,1) interval and a 5% level for the (-4,4) interval.

Similarly, several stocks are statistically significant at other intervals. Xerox Holdings Corp. show significant results at a 5% level for the (-3,-1) interval, with a CAAR of 2,1%. Borg Warner Inc. is significant at a 10% level for the intervals (0,3) and (-4,4), with a CAAR of 1,5% and 2,2% respectively. The Mosaic Company is statistically significant at a 10% level for the (-4,4) interval, with a CAAR of 2,8%. Further, Alliance Data Systems Corp. show significant results at several intervals both before and after the event. Interestingly, for Alliance Data Systems Corp., we find a positive effect before the event, and a negative reversal in the period after the event. This might indicate that the market overvalued the information before the event, and equivalently needs to readjust after the event. The remaining 16 companies show insignificant results for all intervals.

Hence, we provide thorough empirical evidence suggesting that Donald Trump's positive Twitter sentiment affects selected small-cap securities and portfolios. Consequently, we reject the null hypothesis that positive Donald Trump Twitter sentiment does not affect small-cap securities or portfolios.

5.5.2 Negative Donald Trump Twitter sentiment

Table 9 in the appendices shows the results for the negative tweets concerning macroeconomic issues. Similarly, as above, several securities show statistically significant results for the entire event period. Starting with the portfolios, the value-weight portfolio and the equal-weight portfolio are statistically significant at a 1% level for the entire event period. The CAAR of the value-weight portfolio is -1,8%, whereas the CAAR of the equal-weight portfolio is -1,5%. Accordingly, these results imply that when Donald Trump tweets a negative tweet concerning macroeconomic issues, the portfolios would cumulatively decrease by 1,8% and

1,5% across a period of 11 days. There is also a slight negative significant effect in the period after the event for both portfolios.

At the individual security level for negative tweets, we find a significant negative effect for Alliance Data Systems Corp., Nielsen Holdings Plc., and Newell Brands Inc. at a 1% level for the full event interval (-5,5). Their CAAR are -4,8%, -3,6%, and 2,9% respectively. Additionally, all the mentioned securities show significant negative results in the period after the event as well. Kimco Realty Corp. is also significant for the full event window at a 10% level and CAAR of -1,3%. Moreover, Kimco Realty Corp., show significant results for all windows after the event, but none before the event. Especially, immediately after the event, it shows a relatively strong negative effect of -1,3% significant at the 1% level.

Further, several securities are significant at different sub-intervals. Ralph Lauren Corp. and Unum Group both show a statistically significant effect at a 10% level in the period after the event, (1,5). The CAAR of Ralph Lauren and Unum Group is 2,2% and -0,8% respectively in this window. Interestingly, Ralph Lauren sees a negative but statistically insignificant effect in the period before the event. After the event, however, Ralph Lauren has a strong positive significant effect. Hence, we observe that there is a reversal effect on this security. This might indicate that the market, to some extent, adjusts to mispricing after the event. Furthermore, Apache Corp. has a negative CAAR of -2,7% statistically significant at the 10% level in the interval (-5,-1). Also, this security has a positive but insignificant reversal in the period after the event. People's United Financial Inc. has a significant CAAR of -0,7% at the 5% level in the period after the event. Moreover, People's United Financial Inc. also has a similar significant effect for the (-4,4) window at 10% level. The remaining 16 companies are statistically insignificant over the entire event window.

As these results indicate, we can reject the null hypothesis that negative Donald Trump Twitter sentiment does not affect small-cap securities or portfolios.

5.5.3 Cumulative average abnormal return (CAAR) plots

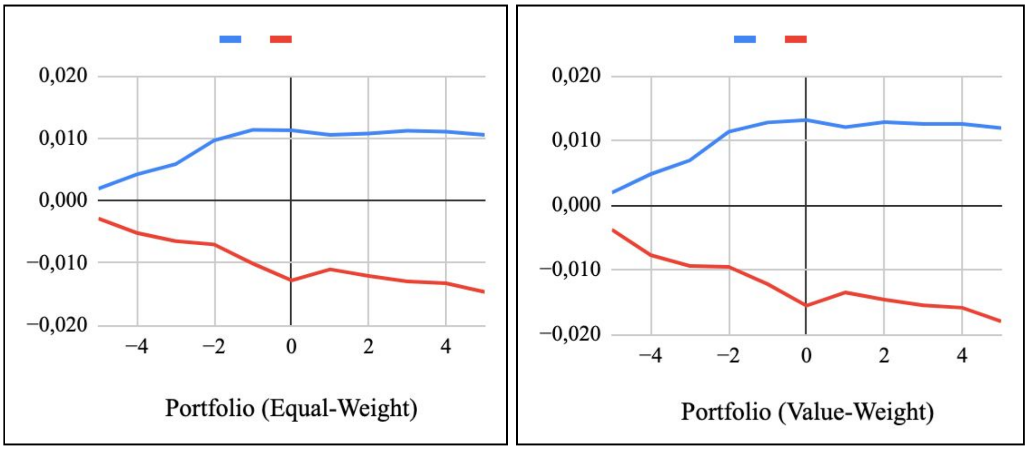
In the following section, we will present the plotted cumulative average abnormal returns for the full event window length. This allows us to analyse them visually and thus better assess whether security prices incorporate event information efficiently. If the cumulative average abnormal returns continue to drift after the event, this would be considered a violation of the semi-strong form of the efficient market hypothesis. Formally, we test the following hypothesis:

H_0 : CAAR is stable after the announcement.

H_A : CAAR continues to drift after the announcement.

We highlight two plots, one for each of the two portfolios. The first plot illustrates the equal-weight plot and the second plot shows the value-weight portfolio. The blue line represents the CAAR which relates to positive tweets. The red line represents the CAAR which relates to negative tweets.

Figure 2: Plot of CAAR for the equal-weighted and value-weighted portfolio



These charts show the plotted cumulative average abnormal return (CAAR) for the value-weighted and the equal-weighted portfolio in the event window. The blue line indicates the CAAR for positive tweets, while the red line indicates the CAAR for negative tweets.

Prior to the event date, the CAAR for positive tweets for both portfolios in Figure 2 seems to drift upward. Accordingly, in the interval (-5,-1) from Table 10, one can see that there is already a statistically significant effect in the period before the actual event date (at day zero). This implies that the market gradually learns about the information of the tweets before they are published. Moreover, this result suggests that information leakage is present for positive tweets. Similarly, for negative tweets, the CAAR for both portfolios drift downward before the event date. From Table 9, we find that there is a statistically significant effect present already before the announcement date for both portfolios in the (-5,-1) interval. Correspondingly, these results suggest that leakage has occurred prior to negative tweets.

Previously in this paper, we addressed the implication of such event date uncertainty. How sure can we be that there has not been any information leakage to the market? Are there other signals, hints or channels which have informed the market what was about to be announced? Several lobbyists, government and administrative personnel, might learn about the outcome of Trump's policies before he announces them on Twitter. Some of this information might reach the market.

Both portfolios are statistically significant for negative sentiment in the interval, (-1,1), surrounding the event. By contrast, both portfolios are insignificant in the same interval for positive Trump sentiment. Furthermore, after the event, more inconsistencies emerge.

In the period after the event for positive tweets, both portfolios show a statistically insignificant negative effect. According to these results, the effect tends to reverse after the announcement very moderately. Moreover, the effect is slightly larger for the value-weight portfolio than the equal-weight portfolio. Based on these findings, it is natural to assume that the effect reversal is most prominent for the largest companies in the sample. A visual assessment of the CAAR-plots for the eight largest companies in the sample further supports this. However, as the CAAR-plots for the portfolios illustrate, the abnormal returns after the event are almost zero, and the CAAR is stable. This indicates that the market rapidly incorporates the information provided by Trump's positive sentiment, consistent with the EMH. Hence, we do not reject the null hypothesis. For the negative tweets, there is a slight negative post-event drift in the CAARs for both portfolios. Quantitatively, the CAAR for both portfolios is approximately -0,2% for the (1,5) interval, significant at a 5% level. Consequently, we can reject the null hypothesis and conclude that the market inadequately adjusts to the new information originating from negative tweet announcements, which is a violation of the EMH.

There are also occurrences of inconsistencies with the EMH for individual securities. For positive tweets, Alliance Data Systems Corp., People's United Financial Inc., and Kimco Realty Corp. all have significant effects in the (1,5) interval. Alliance Data Systems Corp. and Kimco Realty Corp. drift downwards in the period after the event, whereas People's United Financial Inc. continues to drift upwards. This is best illustrated by the CAAR-plots in Table 11 in the appendices. Besides, we find similar effects for The Mosaic Company and Borg Warner Inc., although these results are not strictly significant for the intervals after the event. As noted in the previous section, Alliance Data Systems Corp. has a positive drift before the event, and a significant negative effect reversal in the period after. This might indicate that the market has overvalued information and similarly needs to readjust. These results imply that the new information originating from Donald Trump's negative tweets are hard to incorporate into the stock prices for single securities accurately. Xerox Holdings Inc., Unum Group, and Newell Brands are more or less stable in the period after the event, consistent with the EMH. All the mentioned companies are significant at least one or more intervals, as thoroughly described in the previous section. We do not comment on the remaining companies due to insignificant results.

For negative tweets, Alliance Data Systems Corp., Ralph Lauren Corp., Unum Group, Newell Brands Inc., and Kimco Realty Corp. all show significant results in the interval (1,5). As mentioned in the previous section, Ralph Lauren has a negative drift before the event, and a strong reversal back to zero after the event. This finding might indicate that the market overestimates the consequences of Trump’s tweets concerning macroeconomic issues for Ralph Lauren, and correspondingly needs to revalue the firm equity value later. This is inconsistent with the EMH. Moreover, Alliance Data Systems Corp., Unum Group, Newell

Brands Inc., and Kimco Realty Corp. continues to drift negatively in the period after the event. Nielsen Holdings Plc. can also be mentioned in this regard, as it continues to drift downwards after the event as well. If the event date is included, i.e. for the interval (0,5), there is a significant negative effect. Likewise, these results represent a violation of the EMH. Apache Corp. shows a significant negative effect before the event, but an (insignificant) reversal in the period after. Due to insignificant results, we can not reject the null hypothesis, and we conclude that the market adequately adjusts the firm equity price of Apache Corp., consistent with the EMH. People's United Financial Inc. is more or less stable in the period after, within the boundaries of expected chance deviations. This is consistent with the EMH.

The inference from the above section is that the market tends to less accurately adjust to new information in Donald Trump’s tweets at the individual security level. At the portfolio level for positive tweets, the market rapidly (within one day) adjust and revalue the portfolios according to new information. This is considered consistent with the EMH. For negative tweets, however, the market insufficiently adjusts the portfolios’ values, and the CAAR continues to drift downwards in the period after the event. This is considered a violation of the EMH. Hence, negative sentiment seems to be more challenging for the market to value than positive sentiment.

5.6 Trump tweets and volume traded

Further, we test whether the trading volume is affected by Trump’s tweets for the two portfolios. We calculate the trading volume by aggregating the volume traded for each sample firm, before weighing them equally or by value into the two “portfolios”. In this study, we use log returns as this ensure normalisation of numbers and comparability across the sample firms. We find that days with positive Trump-tweets, on average, generate 1,1% and 2,4% higher volume for the value-weight and equal weight portfolio respectively. On the other hand, days with negative Trump-tweets generate -0,9% and 0% change in aggregate trading volume for the two portfolios. These findings contradict those of Born et al.

(2017), who found higher trading volume patterns for both positive and negative tweets.

The results presented above demand careful interpretation, as volume and stock price relation is subject to much debate. However, several researchers, such as Jonathan Karpoff (1987), argue that there exists an asymmetric relationship between volume and price changes. This theory claims that the relation between volume and positive price changes is stronger than volume and negative price changes. One explanation for this asymmetry is that e.g. short-selling is both costly and unfamiliar to most investors. In turn, this leads to skewness toward the buying of stocks. An absence of buyers results in a lower trading volume, which again leads to negative price adjustments. However, this notion of the volume and stock price relation has also been criticised. Furthermore, even though this asymmetric explanation does correspond well with our findings, we can not draw any conclusions without support from thorough testing and statistical evidence.

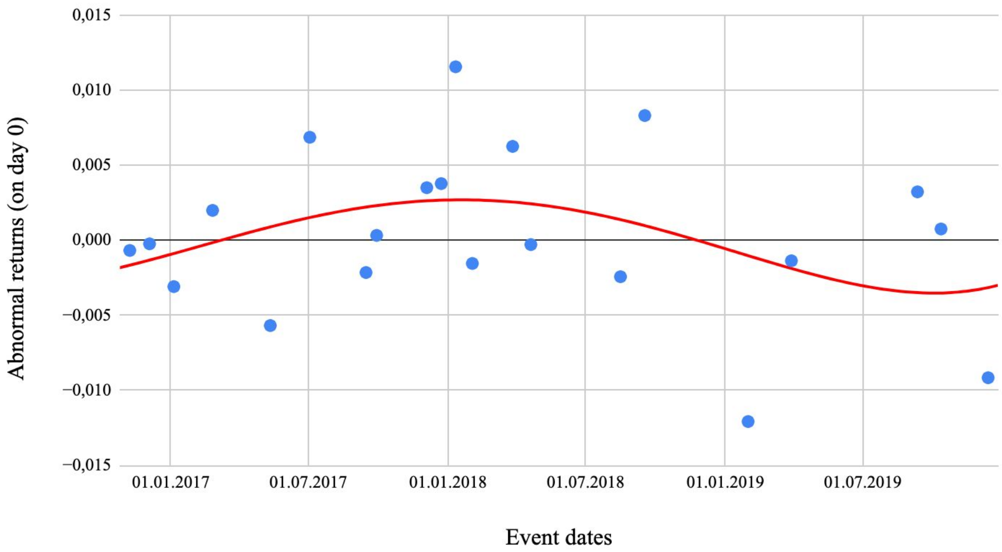
5.7 Trump tweets and market volatility

We proceed to investigate whether there is a relationship between Trump's tweets and volatility. To measure changes in volatility, we choose to apply the Chicago Board Options Exchange Volatility Index (CBOE VIX). CBOE VIX is a measure of expected market volatility and is calculated based on S&P 500 option premiums. Our results show that CBOE VIX on average decreases by 0,27% across the event dates (day 0 in the event window) for positive tweets. Across event dates for negative tweets, the CBOE VIX index increase by an average of 2,02%. However, remark that the VIX is mainly connected to the S&P 500, which is out of the scope of this study. It is, nonetheless, an interesting side note which corresponds well with our results.

5.8 Trump tweets' effect over time

If we plot all the abnormal returns (for a total of 40 tweets) on day 0, we can analyse how Trump's tweets affect the small-cap portfolio over time. Below is an illustration of the value-weight portfolio. Since the equal-weight portfolio is very similar, we proceed using only the value-weight portfolio.

Figure 3: Trump's tweets' effect over time (value-weight portfolio)



This figure illustrates Trump's effect on the value-weight portfolio for each of the 40 tweets. The blue dots indicate the abnormal return caused by Trump's tweets for each event date. The red line is a trendline (fourth-order polynomial regression).

As the trendline illustrates, there is a positive "pull" in the abnormal returns at the start of Trump's term (from the end of 2016 through 2018). On the other hand, there is a likewise negative pull in the latter part of his term, in 2019. This trend is prominent for both negative and positive tweets over time. Thus, we decide to present them on the same chart. It is difficult to determine precisely what causes these pulls in different periods. One possible explanation might be that the sample firms positively receive Trump's policies. In the first period after he took office, Donald Trump frequently tweeted in favour of tax and regulation cuts, increased protectionism, a revised healthcare plan, and less military involvement in foreign countries. The small-cap securities in our study respond well to increased protectionism, as they are more domestic-oriented than larger firms on the S&P 500. This is consistent with the findings of Wagner et al. (2018), which implies that domestic-oriented companies benefit more from the policies of Trump than internationally oriented companies.

One explanation for the negative pull in 2019 is the escalation of the trade war between the U.S. and China. Also, there might be a tendency toward Trump announcing more specific actions in the latter period compared to the start of his presidency. For example, on May 5, 2019, Trump announced that tariffs on 200 billion worth of goods would increase from 10% to 25%. A second example, on August 23, 2019, Trump announced that the remainder of goods from China would be taxed 15%, up from 10%. Both tweets gave a negative effect on the portfolios the same and several subsequent days after they were published. These are examples of tweets concerning specific actions or retaliation in the trade war, which affected the market immediately after publication.

5.9 Robustness checks

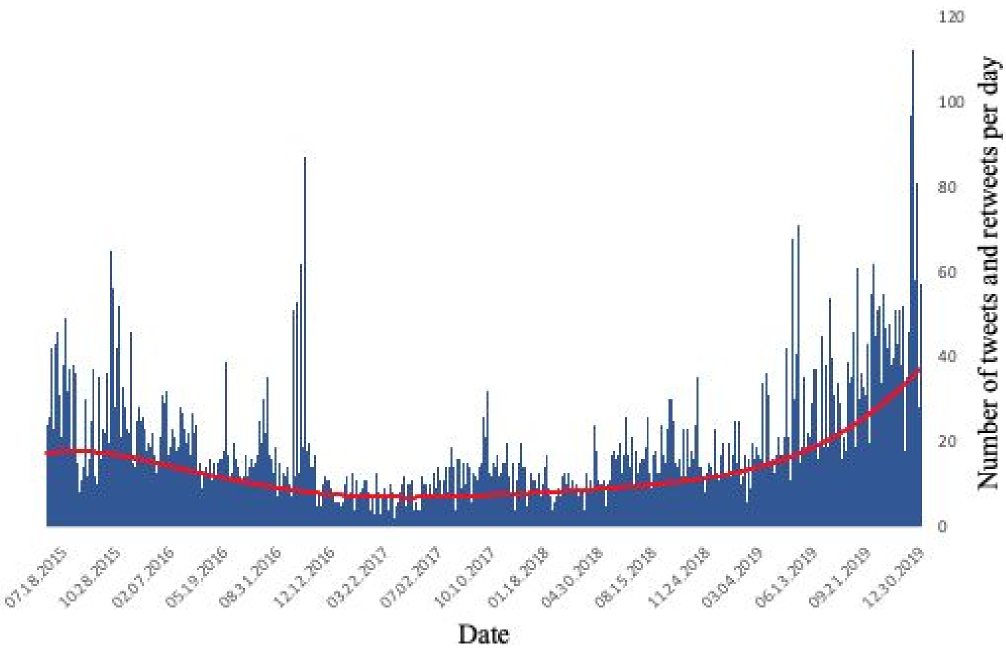
Our data do not contain any prominent or extreme outliers. However, we nonetheless test by removing the three most negative and positive data points for negative tweets and positive tweets, respectively. By data points, we refer to each event-CAR for the entire window for the two portfolios with the most positive or negative effect. The portfolios have a favourable side feature that they can serve as proxies for the overall effect on the sample firms in our study. Thus, by removing the events with the most negative or positive CAR, we test whether the cumulative average abnormal returns or significance is affected. Naturally, we get a somewhat reduced effect, but the significance of our results is not particularly affected. Actually, some of the firms become more significant after the removal of outliers. The two portfolios are still significant at a 1% level after removal. Hence, we consider our results and findings as robust.

Additionally, we assess which securities that primarily cause the effect in the portfolios. We divide the 24 companies into three equal-weighted sub-portfolios according to market capitalisation, each consisting of 8 securities. This analysis follows in Table 12 and 13 in the appendices. According to this analysis, the eight largest companies cause most of the effect in the portfolios. However, for positive tweets, the eight smallest companies show a larger CAAR for the full 11-day interval. The eight medium-sized companies show less effect for positive tweets than for negative tweets. We proceed to exclude the two largest companies with the most negative and positive effect. Accordingly, we exclude Newell Brands Inc. and Alliance Data Systems Corp. for positive tweets and Alliance Data Systems Corp. and Nielsen Holdings Plc. for negative tweets. Naturally, the effect is somewhat reduced, but the results are still significant at a 1% level for both portfolios. Hence, after a thorough assessment, we conclude that our findings are robust.

6 Trump's tweet frequency

We decide to run a separate study on Donald Trump's tweet frequency, using the same procedure as for the main study. However, these findings must be independently assessed, as several of the tweet dates would overlap if otherwise. Nonetheless, we believe that the complementary findings presented in this study might provide a deepened understanding of Donald Trump's impact on the sample firms. Below follows an overview of Trump's Twitter activity and tweet frequency.

Figure 4: Trump's tweet frequency



This chart illustrates Trump's daily Twitter activity in the period between June 2015 and December 2019. The red line is a trendline (sixth-order polynomial regression). The total daily tweet count includes both tweets and retweets.

As the trend line in the picture above illustrates, Trump's daily tweet frequency increased prior to the election in November 2016, dropped significantly in the period after the election, before again increasing steadily toward December 2019. To perform the study on Trump's tweet frequency, we define days that have more than 40 tweets or retweets as our events of interest. However, some small alterations to the methodology are necessary. As we are now dealing with event certainty, there is no reason to include a period before the event (e.g. there can not be leakage before a day with many tweets or retweets). Further, the study only investigates days from 2019. If we include other years, we have to set an independent threshold for inclusion for each year, month, or another smaller interval. Trump has tweeted and retweeted comparatively more in the latter years of his term of office. A flat threshold for inclusion across all the four years would result in 2018-19 becoming very heavy weighed compared to 2016-17. Thus, to avoid such bias and making this complementary study unnecessary complicated, we include only 2019. Lastly, when there is overlap across events, we consistently choose the first date in the series. However, this issue only occurred for a couple of event dates. In total, the study consists of 15 dates with high tweet frequency.

6.1 Empirical Results

Table 5 shows the results for the study of Trump's tweet frequency and its impact on the small-cap portfolios.

Table 5: AAR and CAAR for portfolios (Twitter frequency study)

	Value-weight portfolio	**Equal-weight portfolio**
Day	AAR	AAR
0	0,000	0,000
1	−0,003	−0,002
2	0,000	−0,001
3	0,000	0,000
4	−0,002	−0,001
5	−0,002	−0,001
	CAAR	CAAR
0	0,000	0,000
1	−0,004	−0,003
2	−0,004	−0,004
3	−0,003	−0,004
4	−0,006	−0,005
5	−0,008	−0,006

This table reports the AAR and CAAR for the value-weight and the equal-weight portfolio after days with high tweet counts from Trump. The sample consists of 15 events (days with high Twitter frequency). In this study, the event window is set to 6 days and includes no days before the event due to event certainty (MacKinlay, 1997). We calculate the abnormal returns using Fama and French's (2015) five-factor model as normal return.

Table 5 shows that there is just a minor effect on the portfolios on the event day itself (day 0). However, if Trump tweets after the market close, the effect will not be captured until the next day. This creates some minor event date uncertainty. Nevertheless, we find that there is a negative effect in the subsequent days following event dates with high tweet counts. Table 6 presents the significance tests for two different CAAR-intervals (0,5) and (1,5).

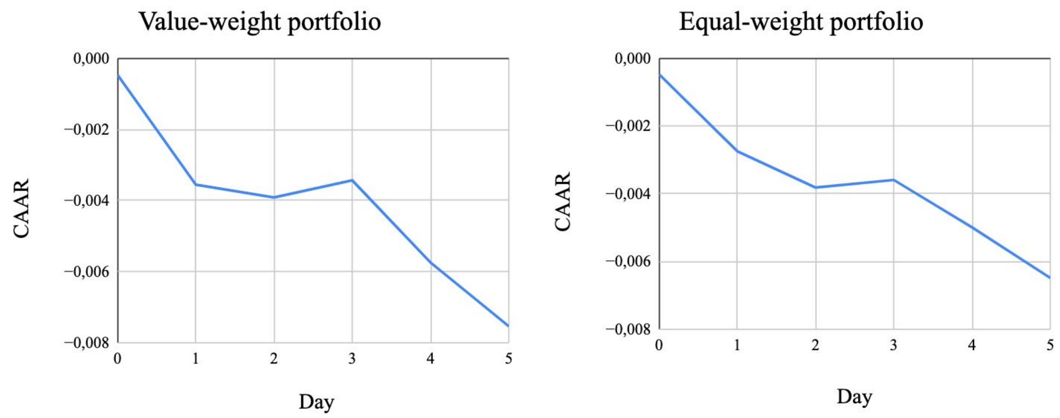
Table 6: Significance tests for portfolios (Twitter frequency study)

		Value-weight portfolio	Equal-weight portfolio
	CAAR	−0,008	−0,006
(0,5)	T-statistic	−2,191	−1,884
	Significance	**	*
	CAAR	−0,007	−0,006
(1,5)	T-statistic	−2,223	−1,888
	Significance	**	*

This table reports the CAAR-significance tests for the value-weight portfolio and the equal-weight portfolio. The table includes two different intervals in the event window, (0,5) and (1,5). The T-statistic is found on the second line, below each associated CAAR. On the third line, ***, **, and * represent a significance level of 1%, 5%, and 10%, respectively. "Insign." indicates that the CAAR is insignificant.

The CAAR for the intervals (0,5) and (1,5) are significant at the 5% level for the value-weight portfolio and at the 10% level for the equal-weight portfolio. This implies that Donald Trump's tweet frequency affect the portfolios in our study. The CAAR for the portfolios is approximately -0,8% and -0,6% respectively for the entire event window. Moreover, for the (1,5) interval, they are -0,7% and -0,6%. This effect can also be illustrated using a CAAR-plot.

Figure 5: CAAR plots for high Trump tweet frequency



The charts above illustrate the CAAR for the value-weight and the equal-weight portfolio after days with high tweet counts from Trump.

As the charts in Figure 5 illustrate, the CAAR continues to drift downward in the period after the event day. Hence, we can reject the null hypothesis that Trump's tweet frequency does not affect the portfolios. Simultaneously, the CAAR continues to drift the period after the event, which is considered a violation of the EMH. This result suggests that investors find it difficult to value and adjust to the increased activity of Trump.

8 Discussion

Several of the sample securities in our study does seem to be affected by Trump's tweets. The effect also seems to persist over multiple days for several of the sample securities. These findings contradict those of Juma'h and Alnsour (2018). However, we also find supportive evidence of pre-event effects. Implicitly, Juma'h and Alnsour (2018) argue that Trump's tweets are information-free events, consistent with the EMH. Our opinion is that Trump's tweets are not strictly information-free events, but that the market gradually learns about the content of the tweets, due to leakage of information. Another explanation for this pre-event effect is that investors have identified specific behavioural patterns with Trump. If Trump's behaviour toward different issues remains sufficiently stable over time, sophisticated investors might predict Trump's responses in advance. Over time these predictions become increasingly accurate, which explains the drift upward or downward before the announcement. If this is the case, the excess returns generated by these investors contradict much of the classical finance theory on the ability to predict future outcomes.

Moreover, there seems to be a correlation between positive tweets and positive abnormal returns and between negative tweets and negative abnormal returns. These results are consistent with the findings of Born et al. (2017). However, we identify some exceptions. For instance, Kimco Realty Corp. accumulates significant negative returns over the full event period for positive tweets. It is natural to assume that this contrasting effect is a result of the content of the tweets rather than Donald Trump's mood. Wagner et al. (2018) found that relative stock prices adjusted to shifts in expectations regarding Trump's trade policies and tax. Similarly, stocks react differently toward news depending on the potential consequences for their business. However, overall, we find that the small-cap sample has a net positive effect across the period for positive tweets and net negative effect for negative tweets. The abnormal returns in the two portfolios capture this effect.

Previously in this paper, the Fama et al. (1969) assumption concerning rational investors was challenged. Shleifer (2000), De Long et al. (1990) and Black (1986), are all advocates for the notion that some investors trade on noise rather than information. Born et al. (2017) also supports this notion in their study of Trump's tweets effect on specific companies. Based on price response, the increase of trading volume, and Google activity, these researchers claim that noise traders are the main cause of the abnormal returns. As problematised in our review of related literature, it can be challenging to reveal and sufficiently prove that noise trading is present in markets and the cause of market anomalies. Thus, we believe that the inferences of Born et al. (2017) might be somewhat premature and lack sufficient evidence. However, some observations are nonetheless worth mentioning in this regard.

The first observation is that the included tweets vary in terms of strict information value for the selected sample securities. It is natural to assume that macroeconomic issues, which are not directly related to the individual companies, are more complex to value, as was the case for Wagner et al. (2018). When news is challenging to value, it might lead to over- or under reactions in the market. This argument alone is not necessarily a violation of the EMH, as some over and under-reaction or chance deviations are expected (Fama, 1970). The second observation is that apparent less informative tweets, occasionally, elicit a more significant effect than more informative tweets on the sample securities. Donald Trump is known for using strong rhetoric in his way of writing. People often tend to focus too much on the strength or extremeness of the evidence, and less on the weight or credence (Barberis, Shleifer & Vishny, 1998; Tversky & Griffin, 1992). This illusion of validity might result in overconfident investors (Tversky & Griffin, 1992; Daniel et al., 1998). In turn, these psychological biases might result in some investors overestimating the consequences of unimportant tweets, and likewise underestimating important tweets.

Thirdly, we observe that information already known to the public also generate abnormal returns when they are commented or mentioned by Trump. Such effects should not occur under efficient markets. Fourthly, these effects might be further amplified by biased self-attribution and overconfidence (Daniel et al., 1998). When investors experience success trading on Trump's tweets, they might continue to trade on similar signals. In turn, these traders create more mispricing. Daniel et al. (1998) suggest that such anomalies are most common for small illiquid stocks, as the illiquidity cause barriers for arbitrageurs to exploit the mispricing effectively. The observations above support the notion that some investors incorporate noise rather than information (Black, 1986), with less concern about the statistical validity or evidence of Trump's statements (Barberis et al., 1998). Moreover, in sum, these observations provide a strong challenge toward market efficiency. However, we can not make any inferences concerning noise trading without more thorough testing.

Lastly, this phenomenon also epitomises an interesting new concern for companies, which we decide to refer to as "opinion leader risk". The definition of an opinion leader is "a person whose opinions about something such as a product or issue have a big influence on the opinions of others" (Cambridge, 2020). In social network analysis, such individuals can often be detected by their actor centrality. Actor centrality commonly refers to how many relations or "ties" an individual has to other actors or "nodes" in the social network (Wasserman & Faust, 1994). If an opinion leader decides to turn against the company, it might impact sales, deals, partnerships, and reputation. Accordingly, this can severely hurt shareholder value. Likewise, if an opinion leader decides to embrace the company, it might contribute to increase shareholder value. Often are the behaviours of such opinion leaders unpredictable. When people tend to overlook the weight of the evidence and focus on the strength (Barberis et al., 1998), opinion leaders might impact the business regardless of the evidence in their accusations. It is no doubt that social media introduce substantial and pervasive changes to communication between organisations, communities, and individuals (Kietzmann et al., 2011). Consequently, this opinion leader risk adds a new dimension to risk management and communication in business. However, this (briefly presented) concept goes well beyond the boundaries of this study and must be pursued in a separate paper.

9 Conclusion

We provide strong empirical evidence that our small-cap portfolios and selected sample firms have been affected by Trump's Twitter sentiment. Overall, we find that positive sentiment tweets generate positive abnormal returns, while negative sentiment tweets generate negative abnormal returns, consistent with the findings of Born et al. (2017). The effect persists multiple days past the announcement date for several of the sample firms, which is considered a violation of the semi-strong form of the EMH. The portfolios are consistent with EMH for positive tweets, as the effect is rapidly incorporated (within one day) after the announcement date. For negative tweets, the EMH is violated, as the cumulative average abnormal returns (CAAR) continue to drift after the event. This indicates that the market finds it more challenging to value negative sentiment than positive sentiment. Moreover, we find that Trump's Twitter sentiment affects stocks across all sizes and multiple industries in our sample. Further, our secondary study provides empirical evidence that Trump's tweet frequency affects the sample portfolios. This effect persists over multiple days and accordingly violates the EMH.

Regarding our complementary findings concerning volume traded, market volatility, and variability in effect across time, we find that trading volume slightly increases for positive tweets and slightly decreases for negative tweets. Moreover, we find that volatility increases for negative tweets and decreases for positive tweets. Regarding variability in effect over time, we observe a positive "pull" in Trump's first period as president and a negative pull toward the end of 2019. These results can be a reaction to the escalation of the trade war between the U.S. and China, as well as a gradual shift toward Trump announcing more concrete actions on Twitter. However, we can not make any inferences about the observed relationships presented in this section without further statistical testing and evidence.

10 Implications

10.1 Methodology and statistical power

There might exist some limitations within the event study methodology, which prevents us from measuring the impact in its entirety. For instance, Trump's tweets may affect the entire market. In this case, the normal return model captures some of the abnormal returns, which might prevent us from detecting the full impact of Trump's tweets. Secondly, as previously stated, security by security analyses might have limited statistical power (MacKinlay, 1997). Mainly, this is due to the high variance in returns for single securities compared to, for instance, portfolios. There exist methods to increase and account for this test power bias. One suggestion is to use the generalised least squares model (GLS) as outlined by Collins and Dent (1984). The benefit of using this model is that it allows for variance shifts and cross-correlations across securities. Another method that might be applicable is the inverse variance weighted average-based test (IVWA) (Graça, 2010). This model addresses the particular weighting of the variance elements, i.e. it applies squarely in situations where the disturbances of the regression models for each firm are contemporaneously uncorrelated. Graça (2010) argues that this model significantly improves the statistical power of the tests.

However, as statistical significance becomes harder to obtain, results are equivalently more reliable. Since our methodology and results are considered more conservative, our evidence is also to be considered more robust. Furthermore, as MacKinlay (1997) also addressed, there is a strong relationship between statistical significance and the R^2 of the regression model. This relationship corresponds well with our results. Our portfolios are well-diversified across both industries and sizes. Accordingly, this leads to a smaller variance of return and therefore, larger R^2 values, compared to those of individual securities. Thus, we get more significant results at the portfolio level. Consequently, there is a higher risk that we have performed type 2 errors (i.e. failed to prove that Trump tweets have an effect) at the individual security level.

10.2 The estimation window

In event studies, one assumes that the estimation period is a measure of an unaffected relationship between the security of interest and the corresponding normal return model data (depending on which model one chooses). However, one could expect that some firm-specific events might affect the company's return and making the security fundamentally different from its estimation period state. Such firm-specific events include significant changes in regulations, technology, dividend policy, consumer behaviour, M&A, or similar, which repeatedly and over time accumulate into a strong negative or a strong positive shift in returns for the focal firm. Firm-specific events are, by nature not captured in the normal return model. However, this bias should be sufficiently solved by increasing the estimation period, under the assumption that similar types of firm-specific events have accumulated within the estimation period as well.

Another implication is the use of a single estimation window before the first event. Usually, one would estimate a normal return model before each event. However, due to little time between events, this was not possible in our study. Overlapping the estimation window and the event window could potentially cause the event returns, having a large influence on the normal return measure. This would be problematic as one within the event study methodology assumes that the event impact is captured by the abnormal returns (MacKinlay, 1997). Since our estimation window is sufficiently large, it is nonetheless considered an adequate measure of a "clean" and representative relationship between the security of interest and the model return data.

10.3 The normal return model

The five-factor model's main problem is its failure to explain the low average returns on small stocks that invest a lot despite low profitability (Fama & French, 2015). This problem is not very prominent in our sample, as most companies have positive net margins. Moreover, the securities that show a statistically significant effect are more profitable and less resource-intensive. Usually, the sample firms which are considered resource-intensive belongs to cyclical industries such as oil and gas. This includes Noble Energy Inc., Apache Corp., National Oilwell Varco Inc. and Helmerich & Payne Inc. However, the investment level in the oil and gas industry usually follows the overall cyclicality of the market. Both airline companies are profitable in the period 2016-2019. Moreover, The Mosaic Company and Quanta Services Inc. are both more or less profitable in the period. The remaining companies are providing services and generally less resource-intensive. Most of these firms are also profitable in the period. Hence, we consider the five-factor model an appropriate measure of normal performance relative to our sample securities.

10.4 Sample securities and sensitivity analysis

Baker and Wurgler (2006) claim that large firms are less sensitive to sentiment than small, unprofitable, or non-dividend-paying stocks. This might be due to there being more available fundamental information about large firms than small firms. Moreover, Shiller (2004) argues that the fundamental value of stocks is hard to measure. Besides, when there is less fundamental information about a company, this further increases the difficulty to value them correctly. Some securities in our sample could potentially be included in the category which Baker and Wurgler (2006) present. However, classical finance theory firmly asserts that sentiment should play no role in the pricing of stocks, regardless of their size, profitability, or dividend policy. Hence, our results are to be considered equally relevant.

10.5 Other implications and final comments

Our study does not consider transaction costs or timing. Moreover, as we use daily closing prices, there is no guarantee that one would be able to buy or sell at these prices. Liquidity barriers are also not considered. Accordingly, we do not engage in any discussions regarding trading strategies or the ability to generate excess returns using Trump's tweets. Neither is this within the scope or ambition of the study. This study is limited to merely assess whether Trump's tweets have a statistically significant impact on financial returns.

11 Suggestions for future research

The area of study concerning the impact of Donald Trump's tweets has several interesting aspects and crossroads, which all can be individually pursued and provided with new valuable insight. As our study measures the impact of Trump's tweets retrospectively, a natural next step would be to conduct a similar study, prospectively, i.e. test if an algorithm with given criteria like the ones presented in this study, generate excess returns. However, this might be challenging as it requires a very accurate and sophisticated high-frequency algorithmic trading model. A second natural next step would be to improve the statistical power of our security by security analysis, as proposed in the section above. By employing test statistics that account for issues concerning covariance across securities and thus allows for aggregation, one contributes to more accurate inferences regarding the impact on stock returns. Additionally, this would be a substantial contribution to the overall event study methodology and implications related to total clustering.

Another suggestion is to measure the impact of Trump's tweets on other asset classes, such as commodities, indexes, or specific exchange-traded funds (ETFs). As can be read in our preliminary thesis, we also considered measuring the impact of Trump's tweets on oil or gold, as well as the CBOE VIX index. Furthermore, one can assess the direct consequences of the content of Trump's tweets on specific sample securities. In this study, we do not thoroughly investigate the direct or indirect consequences of specific content in Trump's tweets for the focal securities. For instance, it would be interesting to know which securities are most affected by the tweets concerning increased tariffs on China's goods or the Federal Reserve's interest rate decisions. Further, one can provide a more profound analysis of whether there exist leakage and where it occurs. Lastly, comovement analysis of stocks would deepen our understanding in terms of how different industries or market capitalisation groups are affected compared to others. All these suggestions would contribute to a better understanding of how Trump or other influential people affect financial markets through Twitter.

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Appendices

Table 7: AAR for companies

Day	The GAP Inc. Positive	The GAP Inc. Negative	National Oilwell Varco Inc. Positive	National Oilwell Varco Inc. Negative	Xerox Holdings Corp. Positive	Xerox Holdings Corp. Negative	Alliance Data Systems Corp. Positive	Alliance Data Systems Corp. Negative	American Airlines Group Inc. Positive	American Airlines Group Inc. Negative	Helmerich & Payne Inc. Positive	Helmerich & Payne Inc. Negative
−5	0,003	−0,007	0,000	−0,005	0,002	−0,002	0,001	−0,013	0,003	−0,007	0,003	−0,009
−4	0,006	0,002	−0,001	−0,006	0,001	0,001	0,001	−0,002	0,005	−0,007	0,006	−0,003
−3	0,002	−0,002	0,007	0,000	0,003	−0,003	0,005	0,000	0,000	−0,003	0,005	−0,003
−2	0,004	−0,002	0,008	0,011	0,017	0,004	0,006	−0,002	0,005	0,001	0,010	0,001
−1	−0,002	−0,001	0,001	−0,004	0,001	0,000	0,000	−0,004	0,000	−0,001	0,002	−0,007
0	0,001	−0,012	0,003	0,000	−0,001	−0,003	0,000	−0,011	−0,002	−0,008	0,000	−0,001
1	0,001	0,006	−0,005	−0,001	0,001	0,008	0,000	−0,001	0,002	−0,002	−0,005	0,001
2	0,007	−0,003	−0,003	0,003	−0,003	−0,007	−0,004	−0,005	0,013	−0,008	−0,009	0,003
3	0,002	−0,001	−0,005	0,000	0,000	0,003	0,001	−0,003	−0,003	0,005	0,003	−0,004
4	−0,006	−0,002	0,005	0,003	−0,004	0,000	−0,004	−0,001	0,002	−0,001	0,002	0,001
5	0,000	−0,001	0,006	−0,004	−0,001	−0,003	−0,006	−0,006	−0,008	−0,001	0,010	−0,009

Day	Nielsen Holdings Plc. Positive	Nielsen Holdings Plc. Negative	Quanta Services Inc. Positive	Quanta Services Inc. Negative	Sealed Air Corp. Positive	Sealed Air Corp. Negative	Ralph Lauren Corp. Positive	Ralph Lauren Corp. Negative	Harley-Davidson Inc. Positive	Harley-Davidson Inc. Negative	Unum Group Positive	Unum Group Negative
−5	0,002	−0,004	0,002	0,000	0,001	−0,001	0,007	0,000	0,001	−0,002	−0,002	0,001
−4	0,002	−0,017	0,004	0,002	−0,003	0,001	0,002	−0,002	0,001	−0,003	0,003	0,000
−3	0,003	−0,001	0,000	0,003	−0,004	−0,002	0,002	−0,003	−0,002	−0,006	0,001	0,000
−2	0,001	−0,001	−0,004	−0,003	−0,001	−0,003	0,002	−0,004	0,004	0,000	0,001	0,003
−1	0,001	0,001	0,005	−0,002	0,002	−0,001	0,001	−0,005	−0,001	−0,004	0,002	−0,003
0	−0,001	−0,004	−0,004	0,002	−0,004	−0,003	0,000	−0,006	0,002	−0,002	0,003	0,001
1	0,001	−0,005	−0,002	0,001	−0,002	0,006	−0,001	0,003	0,002	0,001	0,005	−0,002
2	−0,002	−0,001	0,000	−0,001	0,000	−0,004	0,000	0,000	0,005	−0,002	−0,004	−0,003
3	0,002	0,001	−0,002	0,001	0,001	−0,003	0,008	0,005	0,000	−0,002	0,000	−0,001
4	−0,009	−0,002	0,004	−0,001	0,001	−0,009	0,000	0,002	−0,005	0,000	0,002	−0,001
5	0,001	−0,004	0,003	−0,002	0,001	0,000	−0,004	0,011	−0,006	−0,001	0,000	−0,001

	The Mosaic Company		Noble Energy Inc.		United Airlines Holdings Inc.		Apache Corp.		DXC Technology Company		Newell Brands Inc.	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,001	0,000	−0,001	−0,005	0,003	−0,004	0,003	−0,005	−0,002	0,006	0,006	−0,005
−4	0,006	−0,002	0,008	−0,004	0,002	−0,005	0,005	−0,009	−0,002	0,000	0,006	−0,006
−3	−0,003	−0,001	0,004	0,001	0,005	−0,005	0,005	−0,005	−0,004	0,001	0,001	−0,004
−2	0,003	−0,003	0,011	−0,003	0,009	0,004	0,006	−0,006	0,000	0,001	0,002	0,001
−1	0,008	−0,006	−0,001	−0,008	0,001	−0,002	0,001	−0,003	0,004	−0,005	0,005	0,003
0	0,005	−0,002	0,002	−0,005	−0,004	−0,006	0,003	0,004	−0,002	0,005	0,003	−0,005
1	0,002	−0,001	−0,003	0,008	0,000	0,001	−0,004	0,010	−0,006	−0,001	−0,006	0,010
2	0,000	0,001	−0,007	−0,002	0,012	−0,003	−0,008	0,005	−0,004	−0,005	0,005	0,001
3	0,001	−0,003	−0,008	−0,002	0,000	0,004	0,005	0,001	0,004	−0,002	−0,005	−0,010
4	0,006	0,004	0,002	−0,002	0,006	0,001	0,001	0,004	−0,006	0,003	−0,002	−0,007
5	−0,003	−0,004	0,003	−0,009	−0,004	0,002	0,006	−0,004	0,003	0,003	0,001	−0,006

	People's United Financial Inc.		IPG Photonics Corp.		Flowserve Corp.		Robert Half International Inc.		BorgWarner Inc.		Kimco Realty Corp.	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,000	−0,001	0,006	−0,004	0,004	0,002	0,002	0,000	0,004	−0,003	−0,004	−0,001
−4	0,002	0,000	−0,002	0,008	0,000	−0,001	0,002	0,001	0,001	−0,002	−0,001	−0,002
−3	0,000	0,001	0,001	−0,003	0,003	−0,001	0,000	0,003	0,005	−0,001	0,001	0,002
−2	0,000	−0,001	0,000	−0,013	0,004	−0,001	0,003	0,001	0,003	−0,002	−0,003	0,003
−1	0,001	0,001	0,003	−0,015	0,004	−0,001	0,004	−0,002	0,002	−0,001	−0,004	−0,004
0	0,001	−0,002	−0,008	−0,003	−0,001	−0,004	−0,004	0,001	0,004	0,002	0,002	−0,002
1	0,003	0,001	0,003	0,002	0,000	−0,001	−0,002	−0,001	0,003	0,002	−0,006	−0,002
2	0,002	−0,001	0,000	0,004	0,004	0,002	0,001	−0,004	0,008	0,004	−0,006	−0,002
3	−0,001	−0,003	−0,001	−0,001	0,000	0,001	0,006	−0,001	0,000	−0,001	0,001	−0,006
4	0,002	−0,002	0,003	−0,002	0,001	0,004	−0,001	−0,002	−0,004	0,004	0,001	−0,001
5	0,001	0,000	−0,003	0,003	−0,004	−0,003	−0,001	0,003	−0,008	−0,002	0,002	0,003

This table reports the average abnormal returns (AAR) for the event study of the effect of Trump's twitter sentiment on stock returns. The sample consist of 24 small-cap securites from the S&P 500 Index and 40 tweets collected between 08.11.2016 to 31.12.19. The abnormal returns are calculated using Fama and French's (2015) five-factor model as normal return measure. The tweets have been classified into positive and negative sentiment. The AAR is the sample average abnormal return on each specified day in the event window. These AAR have been aggregated across time, but not across securities due to total clustering (MacKinlay, 1997). Hence, this table reports each security seperately. In the first column, days are denoted relative to the event date, which is zero (0).

Table 8: CAAR for companies

	The GAP Inc.		National Oilwell Varco Inc.		Xerox Holdings Corp.		Alliance Data Systems Corp.		American Airlines Group Inc.		Helmerich & Payne Inc.	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,003	−0,007	0,000	−0,005	0,002	−0,002	0,001	−0,013	0,003	−0,007	0,003	−0,009
−4	0,009	−0,005	−0,001	−0,010	0,003	−0,001	0,002	−0,015	0,008	−0,014	0,009	−0,013
−3	0,011	−0,007	0,005	−0,011	0,006	−0,004	0,007	−0,015	0,008	−0,017	0,014	−0,016
−2	0,015	−0,009	0,013	0,000	0,023	0,001	0,013	−0,017	0,013	−0,016	0,024	−0,014
−1	0,014	−0,010	0,014	−0,004	0,024	0,000	0,013	−0,021	0,013	−0,018	0,026	−0,021
0	0,015	−0,022	0,017	−0,004	0,023	−0,003	0,012	−0,031	0,011	−0,026	0,026	−0,022
1	0,016	−0,016	0,011	−0,005	0,024	0,006	0,013	−0,033	0,013	−0,028	0,022	−0,021
2	0,022	−0,019	0,009	−0,002	0,020	−0,001	0,008	−0,038	0,026	−0,035	0,013	−0,018
3	0,024	−0,020	0,004	−0,002	0,020	0,002	0,009	−0,040	0,022	−0,031	0,016	−0,022
4	0,018	−0,021	0,009	0,001	0,017	0,002	0,005	−0,042	0,025	−0,031	0,018	−0,022
5	0,018	−0,022	0,016	−0,003	0,016	0,000	−0,002	−0,048	0,017	−0,032	0,028	−0,031

	Nielsen Holdings Plc.		Quanta Services Inc.		Sealed Air Corp.		Ralph Lauren Corp.		Harley-Davidson Inc.		Unum Group	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,002	−0,004	0,002	0,000	0,001	−0,001	0,007	0,000	0,001	−0,002	−0,002	0,001
−4	0,005	−0,022	0,006	0,002	−0,002	0,001	0,009	−0,002	0,002	−0,005	0,001	0,001
−3	0,007	−0,022	0,006	0,005	−0,006	−0,002	0,011	−0,005	0,000	−0,011	0,002	0,001
−2	0,008	−0,023	0,002	0,002	−0,007	−0,005	0,013	−0,010	0,004	−0,011	0,004	0,004
−1	0,010	−0,022	0,007	0,000	−0,005	−0,005	0,014	−0,015	0,003	−0,016	0,006	0,001
0	0,008	−0,026	0,003	0,002	−0,010	−0,009	0,014	−0,022	0,005	−0,017	0,009	0,002
1	0,009	−0,031	0,001	0,003	−0,012	−0,003	0,013	−0,018	0,007	−0,016	0,014	0,000
2	0,008	−0,032	0,001	0,002	−0,012	−0,007	0,014	−0,018	0,012	−0,018	0,010	−0,002
3	0,009	−0,030	−0,001	0,003	−0,010	−0,010	0,022	−0,013	0,013	−0,020	0,010	−0,003
4	0,000	−0,032	0,003	0,001	−0,010	−0,018	0,022	−0,011	0,008	−0,020	0,012	−0,004
5	0,001	−0,036	0,006	0,000	−0,008	−0,018	0,018	0,000	0,002	−0,021	0,011	−0,006

	The Mosaic Company		Noble Energy Inc.		United Airlines Holdings Inc.		Apache Corp.		DXC Technology Company		Newell Brands Inc.	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,001	0,000	−0,001	−0,005	0,003	−0,004	0,003	−0,005	−0,002	0,006	0,006	−0,005
−4	0,008	−0,002	0,007	−0,009	0,006	−0,009	0,008	−0,014	−0,004	0,005	0,012	−0,011
−3	0,005	−0,003	0,011	−0,008	0,010	−0,014	0,013	−0,019	−0,008	0,007	0,013	−0,016
−2	0,008	−0,006	0,022	−0,011	0,019	−0,009	0,018	−0,025	−0,008	0,007	0,015	−0,015
−1	0,015	−0,012	0,022	−0,018	0,020	−0,012	0,019	−0,027	−0,004	0,002	0,020	−0,011
0	0,021	−0,014	0,023	−0,023	0,016	−0,018	0,022	−0,024	−0,006	0,007	0,024	−0,017
1	0,023	−0,015	0,020	−0,015	0,016	−0,017	0,018	−0,014	−0,012	0,006	0,017	−0,006
2	0,023	−0,013	0,013	−0,017	0,029	−0,020	0,009	−0,009	−0,016	0,002	0,022	−0,005
3	0,024	−0,016	0,005	−0,019	0,029	−0,016	0,014	−0,008	−0,012	−0,001	0,017	−0,016
4	0,030	−0,012	0,008	−0,021	0,035	−0,016	0,015	−0,004	−0,018	0,002	0,016	−0,023
5	0,027	−0,016	0,011	−0,029	0,031	−0,014	0,021	−0,008	−0,015	0,005	0,017	−0,029

	People's United Financial Inc.		IPG Photonics Corp.		Flowserve Corp.		Robert Half International Inc.		BorgWarner Inc.		Kimco Realty Corp.	
Day	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,000	−0,001	0,006	−0,004	0,004	0,002	0,002	0,000	0,004	−0,003	−0,004	−0,001
−4	0,001	−0,001	0,004	0,004	0,004	0,001	0,004	0,002	0,005	−0,005	−0,006	−0,003
−3	0,002	0,000	0,004	0,001	0,007	0,000	0,004	0,005	0,010	−0,006	−0,004	−0,001
−2	0,002	−0,001	0,005	−0,012	0,011	−0,001	0,007	0,006	0,013	−0,008	−0,007	0,003
−1	0,003	0,000	0,008	−0,027	0,015	−0,002	0,012	0,004	0,015	−0,009	−0,010	−0,002
0	0,003	−0,002	0,000	−0,029	0,014	−0,006	0,008	0,005	0,019	−0,006	−0,008	−0,004
1	0,007	−0,002	0,003	−0,027	0,014	−0,007	0,006	0,003	0,022	−0,005	−0,015	−0,006
2	0,009	−0,002	0,003	−0,023	0,018	−0,005	0,007	−0,001	0,030	−0,001	−0,021	−0,008
3	0,008	−0,005	0,002	−0,024	0,018	−0,004	0,013	−0,001	0,030	−0,001	−0,020	−0,014
4	0,010	−0,008	0,005	−0,026	0,019	0,000	0,012	−0,003	0,026	0,003	−0,019	−0,015
5	0,011	−0,007	0,001	−0,023	0,015	−0,003	0,011	0,000	0,018	0,001	−0,017	−0,013

This table reports cumulative average abnormal returns (CAAR) for the event study of the effect of Trump's twitter sentiment on stock returns. The sample consist of 24 small-cap securites from the S&P 500 Index and 40 tweets collected between 08.11.2016 to 31.12.19. The abnormal returns are calculated using Fama and French's (2015) five-factor model as normal return measure. The tweets have been classified into positive and negative sentiment. CAAR is the cumulative sample average abnormal return from day -5 until each specified day in the event window. In the first column, days are denoted relative to the event date, which is zero (0).

Table 9: CAAR in-depth analysis (Negative Tweets)

	Company	The GAP Inc.	National Oilwell Varco Inc.	Xerox Holdings Corp.	Alliance Data Systems Corp.	American Airlines Group Inc.	Helmerich & Payne Inc.	Nielsen Holdings Plc.
	CAAR	**−0,022**	**−0,003**	**0,000**	**−0,048**	**−0,032**	**−0,031**	**−0,036**
(-5,5)	T-statistic	−1,139	−0,188	−0,027	−5,198	−0,579	−1,158	−3,374
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	***
	CAAR	**−0,010**	**−0,004**	**0,000**	**−0,021**	**−0,018**	**−0,021**	**−0,022**
(-5,-1)	T-statistic	−0,750	−0,307	0,021	−3,157	−0,452	−1,126	−2,975
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	***
	CAAR	**−0,005**	**0,007**	**0,001**	**−0,006**	**−0,004**	**−0,009**	**−0,001**
(-3,-1)	T-statistic	−0,462	0,716	0,091	−1,064	−0,123	−0,553	−0,119
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,010**	**0,002**	**0,002**	**−0,020**	**−0,013**	**−0,001**	**−0,008**
(0,3)	T-statistic	−0,766	0,149	0,210	−3,328	−0,369	−0,056	−1,174
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	Insign.
	CAAR	**−0,012**	**0,000**	**−0,001**	**−0,027**	**−0,014**	**−0,010**	**−0,013**
(0,5)	T-statistic	−0,797	0,038	−0,054	−3,883	−0,340	−0,473	−1,664
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	*
	CAAR	**−0,006**	**−0,005**	**0,005**	**−0,016**	**−0,011**	**−0,006**	**−0,008**
(-1,1)	T-statistic	−0,552	−0,567	0,559	−2,981	−0,361	−0,414	−1,258
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	Insign.
	CAAR	**0,002**	**0,002**	**0,005**	**−0,009**	**−0,005**	**0,000**	**−0,004**
(1,3)	T-statistic	0,175	0,189	0,561	−1,673	−0,149	−0,018	−0,683
	Significance	Insign.	Insign.	Insign.	*	Insign.	Insign.	Insign.
	CAAR	**0,000**	**0,001**	**0,002**	**−0,016**	**−0,006**	**−0,009**	**−0,010**
(1,5)	T-statistic	−0,019	0,059	0,207	−2,521	−0,152	−0,475	−1,282
	Significance	Insign.	Insign.	Insign.	**	Insign.	Insign.	Insign.
	CAAR	**−0,015**	**0,008**	**0,003**	**−0,025**	**−0,017**	**−0,010**	**−0,009**
(-3,-3)	T-statistic	−0,933	0,624	0,231	−3,384	−0,379	−0,435	−1,013
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	Insign.
	CAAR	**−0,014**	**0,006**	**0,004**	**−0,028**	**−0,024**	**−0,012**	**−0,028**
(-4,4)	T-statistic	−0,814	0,373	0,268	−3,388	−0,488	−0,506	−2,899
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	***

	Company	Quanta Services Inc.	Sealed Air Corp.	Ralph Lauren Corp.	Harley-Davidson Inc.	Unum Group	The Mosaic Company	Noble Energy Inc.
	CAAR	**0,000**	**−0,018**	**0,000**	**−0,021**	**−0,006**	**−0,016**	**−0,029**
(-5,5)	T-statistic	−0,022	−1,006	0,017	−1,471	−0,921	−0,882	−1,569
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,000**	**−0,005**	**−0,015**	**−0,016**	**0,001**	**−0,012**	**−0,018**
(-5,-1)	T-statistic	0,027	−0,407	−1,193	−1,529	0,273	−0,938	−1,388
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,002**	**−0,006**	**−0,013**	**−0,010**	**0,000**	**−0,010**	**−0,009**
(-3,-1)	T-statistic	−0,121	−0,556	−1,240	−1,236	0,004	−0,957	−0,848
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,002**	**−0,004**	**0,002**	**−0,004**	**−0,004**	**−0,004**	**−0,001**
(0,3)	T-statistic	0,157	−0,373	0,203	−0,425	−1,126	−0,383	−0,059
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,001**	**−0,013**	**0,016**	**−0,006**	**−0,007**	**−0,004**	**−0,011**
(0,5)	T-statistic	−0,054	−0,940	1,128	−0,511	−1,458	−0,286	−0,770
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,001**	**0,002**	**−0,008**	**−0,005**	**−0,004**	**−0,009**	**−0,004**
(-1,1)	T-statistic	0,045	0,184	−0,811	−0,589	−1,111	−0,869	−0,413
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,000**	**−0,001**	**0,009**	**−0,002**	**−0,005**	**−0,002**	**0,004**
(1,3)	T-statistic	0,027	−0,098	0,840	−0,295	−1,544	−0,237	0,358
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,003**	**−0,010**	**0,022**	**−0,004**	**−0,008**	**−0,002**	**−0,006**
(1,5)	T-statistic	−0,179	−0,756	1,719	−0,405	−1,808	−0,153	−0,486
	Significance	Insign.	Insign.	*	Insign.	*	Insign.	Insign.
	CAAR	**0,001**	**−0,010**	**−0,011**	**−0,014**	**−0,004**	**−0,014**	**−0,010**
(-3,-3)	T-statistic	0,039	−0,688	−0,717	−1,210	−0,888	−0,979	−0,646
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,002**	**−0,018**	**−0,011**	**−0,017**	**−0,005**	**−0,012**	**−0,015**
(-4,4)	T-statistic	0,090	−1,072	−0,646	−1,316	−0,933	−0,729	−0,902
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.

	Company	United Airlines Holdings Inc.	Apache Corp.	DXC Technology Company	Newell Brands Inc.	People's United Financial Inc.	IPG Photonics Corp.	Flowserve Corp.
(-5,5)	**CAAR**	**−0,014**	**−0,008**	**0,005**	**−0,029**	**−0,007**	**−0,023**	**−0,003**
	T-statistic	−0,300	−0,379	0,240	−3,225	−1,600	−0,650	−0,240
	Significance	Insign.	Insign.	Insign.	***	Insign.	Insign.	Insign.
(-5,-1)	**CAAR**	**−0,012**	**−0,027**	**0,002**	**−0,011**	**0,000**	**−0,027**	**−0,002**
	T-statistic	−0,360	−1,909	0,151	−1,765	−0,026	−1,063	−0,258
	Significance	Insign.	*	Insign.	*	Insign.	Insign.	Insign.
(-3,-1)	**CAAR**	**−0,002**	**−0,014**	**−0,003**	**0,000**	**0,001**	**−0,031**	**−0,004**
	T-statistic	−0,095	−1,182	−0,249	0,019	0,368	−1,491	−0,535
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(0,3)	**CAAR**	**−0,005**	**0,020**	**−0,003**	**−0,005**	**−0,005**	**0,003**	**−0,002**
	T-statistic	−0,164	1,508	−0,206	−0,810	−1,757	0,113	−0,202
	Significance	Insign.	Insign.	Insign.	Insign.	*	Insign.	Insign.
(0,5)	**CAAR**	**−0,002**	**0,020**	**0,003**	**−0,018**	**−0,007**	**0,004**	**−0,001**
	T-statistic	−0,059	1,270	0,174	−2,589	−2,071	0,133	−0,076
	Significance	Insign.	Insign.	Insign.	***	**	Insign.	Insign.
(-1,1)	**CAAR**	**−0,008**	**0,011**	**−0,001**	**0,008**	**−0,001**	**−0,015**	**−0,006**
	T-statistic	−0,309	0,952	−0,098	1,615	−0,369	−0,747	−0,912
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(1,3)	**CAAR**	**0,001**	**0,016**	**−0,008**	**0,001**	**−0,003**	**0,005**	**0,003**
	T-statistic	0,057	1,374	−0,622	0,152	−1,042	0,254	0,392
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(1,5)	**CAAR**	**0,004**	**0,016**	**−0,002**	**−0,012**	**−0,005**	**0,006**	**0,003**
	T-statistic	0,132	1,118	−0,131	−1,933	−1,483	0,248	0,422
	Significance	Insign.	Insign.	Insign.	*	Insign.	Insign.	Insign.
(-3,-3)	**CAAR**	**−0,007**	**0,006**	**−0,006**	**−0,005**	**−0,004**	**−0,028**	**−0,005**
	T-statistic	−0,197	0,356	−0,340	−0,627	−1,129	−0,965	−0,538
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(-4,4)	**CAAR**	**−0,012**	**0,001**	**−0,004**	**−0,018**	**−0,007**	**−0,022**	**−0,002**
	T-statistic	−0,282	0,028	−0,192	−2,191	−1,651	−0,688	−0,155
	Significance	Insign.	Insign.	Insign.	**	*	Insign.	Insign.

	Company	Robert Half International Inc.	BorgWarner Inc.	Kimco Realty Corp.	PORTFOLIO (VW)	PORTFOLIO (EW)
	CAAR	**0,000**	**0,001**	**−0,013**	**−0,018**	**−0,015**
(-5,5)	T-statistic	0,046	0,062	−1,891	−10,664	−12,937
	Significance	Insign.	Insign.	*	***	***
	CAAR	**0,004**	**−0,009**	**−0,002**	**−0,012**	**−0,010**
(-5,-1)	T-statistic	0,520	−0,938	−0,324	−10,247	−12,639
	Significance	Insign.	Insign.	Insign.	***	***
	CAAR	**0,002**	**−0,003**	**0,002**	**−0,004**	**−0,005**
(-3,-1)	T-statistic	0,381	−0,441	0,397	−4,580	−7,518
	Significance	Insign.	Insign.	Insign.	***	***
	CAAR	**−0,005**	**0,007**	**−0,013**	**−0,003**	**−0,003**
(0,3)	T-statistic	−0,725	0,859	−2,919	−3,021	−3,883
	Significance	Insign.	Insign.	***	***	***
	CAAR	**−0,004**	**0,010**	**−0,011**	**−0,006**	**−0,005**
(0,5)	T-statistic	−0,422	0,950	−2,175	−4,476	−5,237
	Significance	Insign.	Insign.	**	***	***
	CAAR	**−0,003**	**0,004**	**−0,008**	**−0,004**	**−0,004**
(-1,1)	T-statistic	−0,435	0,465	−2,160	−4,074	−6,119
	Significance	Insign.	Insign.	**	***	***
	CAAR	**−0,006**	**0,005**	**−0,011**	**0,000**	**0,000**
(1,3)	T-statistic	−0,932	0,638	−2,734	0,059	−0,227
	Significance	Insign.	Insign.	***	Insign.	Insign.
	CAAR	**−0,004**	**0,007**	**−0,009**	**−0,002**	**−0,002**
(1,5)	T-statistic	−0,554	0,763	−1,917	−2,029	−2,298
	Significance	Insign.	Insign.	*	**	**
	CAAR	**−0,003**	**0,004**	**−0,011**	**−0,008**	**−0,008**
(-3,-3)	T-statistic	−0,304	0,367	−2,026	−5,627	−8,386
	Significance	Insign.	Insign.	**	***	***
	CAAR	**−0,003**	**0,006**	**−0,014**	**−0,012**	**−0,010**
(-4,4)	T-statistic	−0,306	0,505	−2,242	−7,828	−10,035
	Significance	Insign.	Insign.	**	***	***

This table reports the cumulative average abnormal return (CAAR) for tweets with negative Trump sentiment for each of the 24 sample securities and the two portfolios in our study. The CAAR is aggregated across time, but not across securities due to total clustering (MacKinlay, 1997). Fama and French's (2015) five-factor model is employed as our normal performance measure. The sample period is 08.11.16 - 31.12.19. The first event window presented, (-5,5), represents the entire event window. The other windows are smaller intervals either before, during, or after the event. The T-statistic is found on the second line, below each associated CAAR. On the third line, ***, **, and * represent a significance level of 1%, 5%, and 10%, respectively. “Insign.” indicates that the CAAR is insignificant.

Table 10: CAAR in-depth analysis (Positive Tweets)

	Company	The GAP Inc.	National Oilwell Varco Inc.	Xerox Holdings Corp.	Alliance Data Systems Corp.	American Airlines Group Inc.	Helmerich & Payne Inc.	Nielsen Holdings Plc.
	CAAR	**0,018**	**0,016**	**0,016**	**−0,002**	**0,017**	**0,028**	**0,001**
(-5,5)	T-statistic	0,913	0,938	1,024	−0,168	0,307	1,055	0,131
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,014**	**0,014**	**0,024**	**0,013**	**0,013**	**0,026**	**0,010**
(-5,-1)	T-statistic	0,998	0,514	1,063	1,077	0,228	0,804	0,847
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,004**	**0,015**	**0,021**	**0,011**	**0,004**	**0,017**	**0,005**
(-3,-1)	T-statistic	0,388	1,568	2,415	1,986	0,142	1,109	0,835
	Significance	Insign.	Insign.	**	**	Insign.	Insign.	Insign.
	CAAR	**0,010**	**−0,009**	**−0,004**	**−0,004**	**0,010**	**−0,010**	**0,000**
(0,3)	T-statistic	0,807	−0,861	−0,381	−0,618	0,279	−0,573	−0,036
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,004**	**0,002**	**−0,008**	**−0,014**	**0,004**	**0,002**	**−0,008**
(0,5)	T-statistic	0,271	0,157	−0,726	−2,023	0,103	0,102	−1,017
	Significance	Insign.	Insign.	Insign.	**	Insign.	Insign.	Insign.
	CAAR	**0,000**	**−0,001**	**0,001**	**0,000**	**0,000**	**−0,003**	**0,001**
(-1,1)	T-statistic	0,031	−0,156	0,111	0,015	0,005	−0,162	0,169
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,009**	**−0,012**	**−0,003**	**−0,003**	**0,012**	**−0,010**	**0,001**
(1,3)	T-statistic	0,530	−0,884	−0,161	−0,468	0,302	−0,598	0,036
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,003**	**−0,001**	**−0,007**	**−0,014**	**0,006**	**0,002**	**−0,007**
(1,5)	T-statistic	0,222	−0,096	−0,670	−2,150	0,153	0,108	−0,951
	Significance	Insign.	Insign.	Insign.	**	Insign.	Insign.	Insign.
	CAAR	**0,002**	**−0,005**	**0,000**	**0,001**	**−0,003**	**0,003**	**0,002**
(-3,-3)	T-statistic	0,097	−0,333	0,000	0,103	−0,077	0,146	0,210
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,015**	**0,010**	**0,015**	**0,004**	**0,022**	**0,015**	**−0,002**
(-4,4)	T-statistic	0,835	0,643	1,064	0,458	0,432	0,613	−0,190
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.

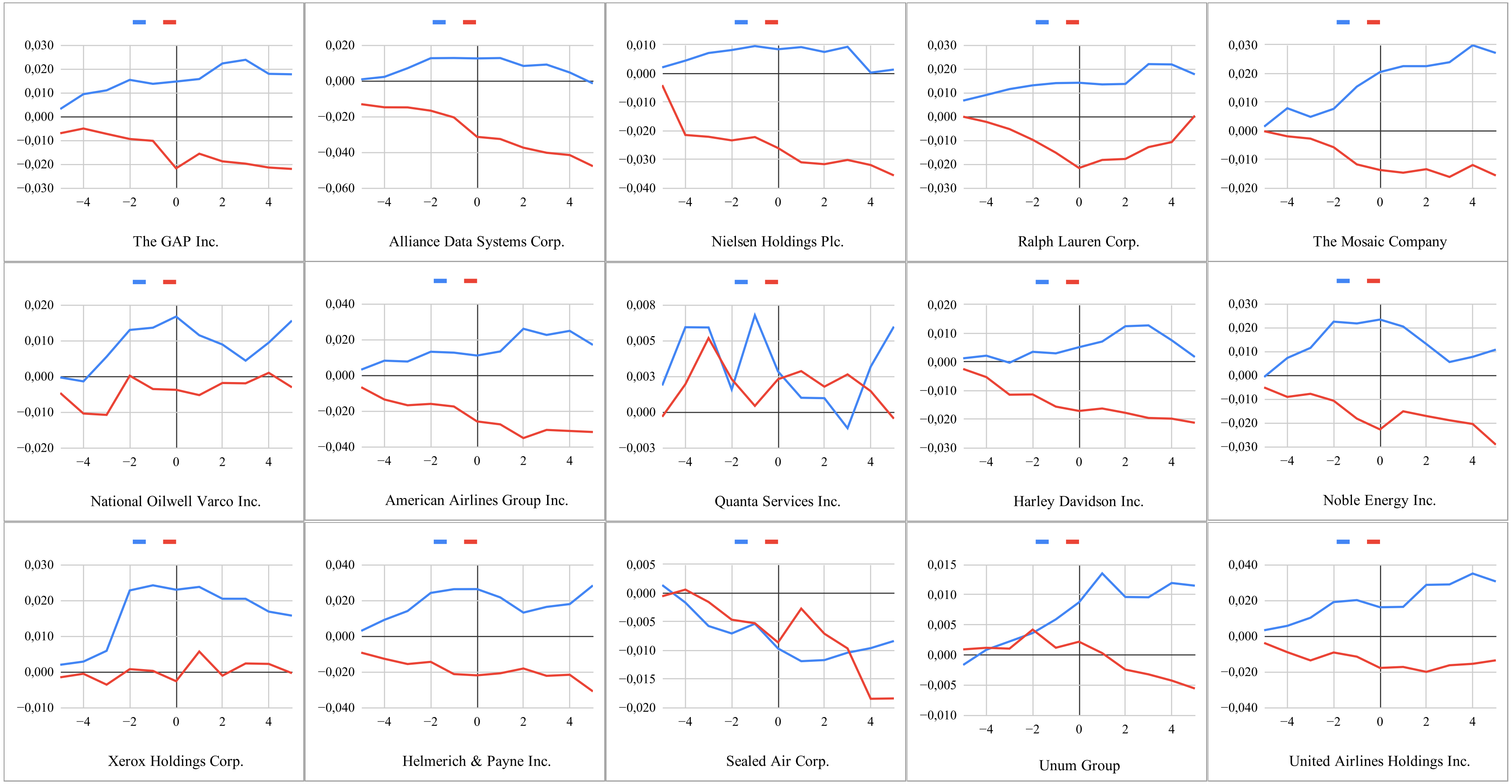
	Company	Quanta Services Inc.	Sealed Air Corp.	Ralph Lauren Corp.	Harley-Davidson Inc.	Unum Group	The Mosaic Company	Noble Energy Inc.
	CAAR	**0,006**	**−0,008**	**0,018**	**0,002**	**0,011**	**0,027**	**0,011**
(-5,5)	T-statistic	0,274	−0,457	0,976	0,119	1,888	1,529	0,575
	Significance	Insign.	Insign.	Insign.	Insign.	*	Insign.	Insign.
	CAAR	**0,007**	**−0,005**	**0,014**	**0,003**	**0,006**	**0,015**	**0,022**
(-5,-1)	T-statistic	0,286	−0,285	0,846	0,188	0,506	0,591	0,941
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,001**	**−0,004**	**0,005**	**0,001**	**0,005**	**0,008**	**0,014**
(-3,-1)	T-statistic	0,067	−0,349	0,477	0,098	1,439	0,737	1,349
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,008**	**−0,005**	**0,008**	**0,010**	**0,004**	**0,009**	**−0,016**
(0,3)	T-statistic	−0,562	−0,428	0,684	1,047	0,934	0,743	−1,348
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,001**	**−0,003**	**0,004**	**−0,001**	**0,006**	**0,012**	**−0,011**
(0,5)	T-statistic	−0,048	−0,216	0,266	−0,115	1,205	0,867	−0,772
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,001**	**−0,005**	**0,000**	**0,004**	**0,010**	**0,015**	**−0,002**
(-1,1)	T-statistic	−0,046	−0,458	0,037	0,431	2,821	1,456	−0,190
	Significance	Insign.	Insign.	Insign.	Insign.	***	Insign.	Insign.
	CAAR	**−0,004**	**−0,001**	**0,008**	**0,008**	**0,001**	**0,003**	**−0,018**
(1,3)	T-statistic	−0,204	−0,157	0,212	0,675	0,620	0,245	−0,963
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,003**	**0,001**	**0,004**	**−0,003**	**0,003**	**0,007**	**−0,013**
(1,5)	T-statistic	0,204	0,101	0,276	−0,334	0,644	0,531	−0,958
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,002**	**0,001**	**0,008**	**0,000**	**0,000**	**0,001**	**−0,008**
(-3,-3)	T-statistic	−0,118	0,086	0,565	0,025	−0,009	0,095	−0,497
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,001**	**−0,011**	**0,015**	**0,006**	**0,014**	**0,028**	**0,008**
(-4,4)	T-statistic	0,066	−0,659	0,920	0,477	2,451	1,754	0,497
	Significance	Insign.	Insign.	Insign.	Insign.	**	*	Insign.

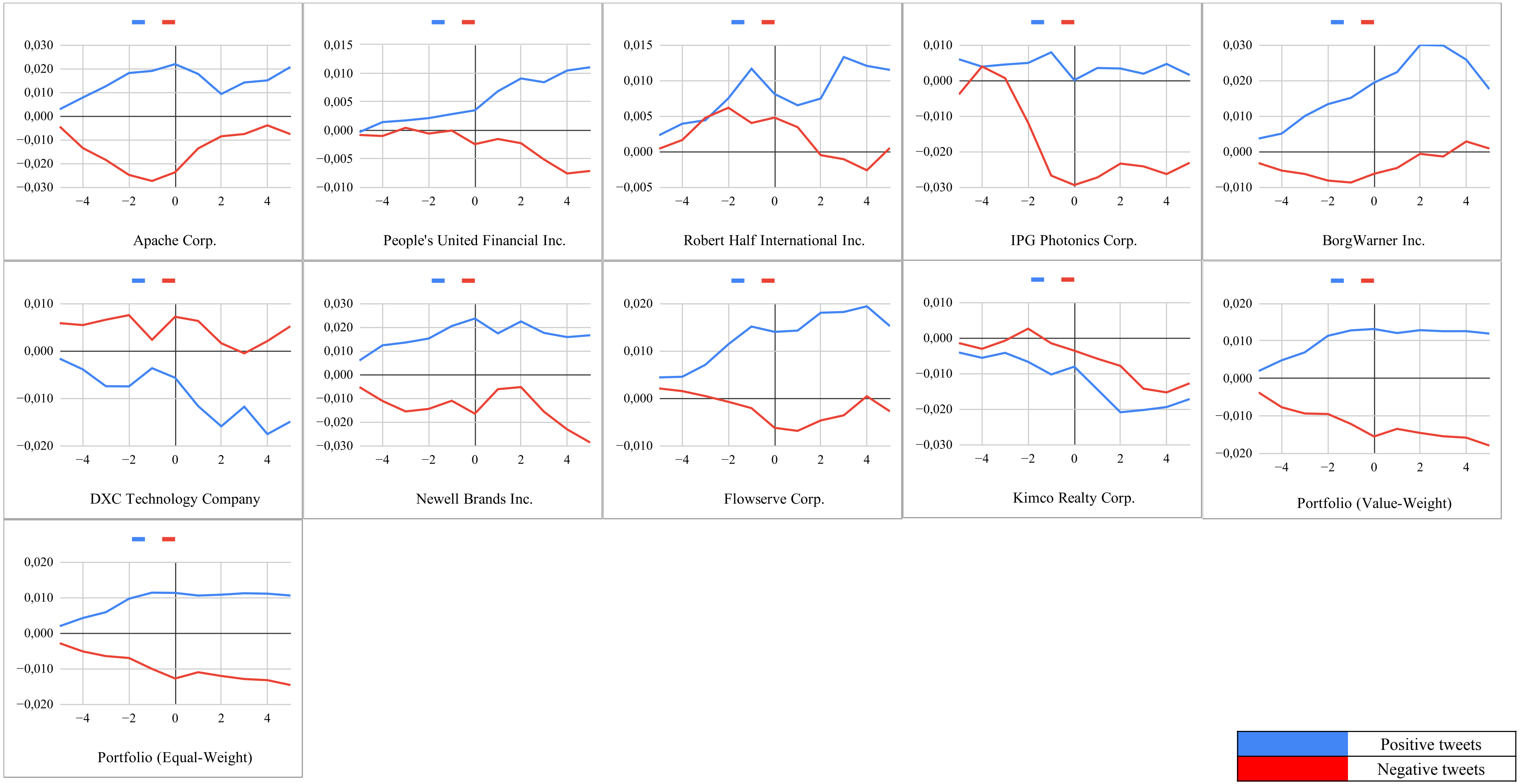
	Company	United Airlines Holdings Inc.	Apache Corp.	DXC Technology Company	Newell Brands Inc.	People's United Financial Inc.	IPG Photonics Corp.	Flowserve Corp.
(-5,5)	**CAAR**	**0,031**	**0,021**	**−0,015**	**0,017**	**0,011**	**0,001**	**0,015**
	T-statistic	0,672	1,015	−0,695	1,852	2,460	0,042	1,305
	Significance	Insign.	Insign.	Insign.	*	**	Insign.	Insign.
(-5,-1)	**CAAR**	**0,020**	**0,019**	**−0,004**	**0,020**	**0,003**	**0,008**	**0,015**
	T-statistic	0,362	0,836	−0,320	2,129	0,483	0,214	1,029
	Significance	Insign.	Insign.	Insign.	**	Insign.	Insign.	Insign.
(-3,-1)	**CAAR**	**0,014**	**0,011**	**0,000**	**0,008**	**0,001**	**0,004**	**0,011**
	T-statistic	0,550	0,956	0,020	1,581	0,540	0,196	1,576
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(0,3)	**CAAR**	**0,009**	**−0,005**	**−0,008**	**−0,003**	**0,006**	**−0,006**	**0,003**
	T-statistic	0,299	−0,371	−0,586	−0,506	1,934	−0,262	0,409
	Significance	Insign.	Insign.	Insign.	Insign.	*	Insign.	Insign.
(0,5)	**CAAR**	**0,010**	**0,002**	**−0,011**	**−0,004**	**0,008**	**−0,006**	**0,000**
	T-statistic	0,301	0,108	−0,685	−0,572	2,402	−0,234	0,011
	Significance	Insign.	Insign.	Insign.	Insign.	**	Insign.	Insign.
(-1,1)	**CAAR**	**−0,003**	**0,000**	**−0,004**	**0,002**	**0,005**	**−0,001**	**0,003**
	T-statistic	−0,103	−0,034	−0,335	0,425	1,823	−0,069	0,427
	Significance	Insign.	Insign.	Insign.	Insign.	*	Insign.	Insign.
(1,3)	**CAAR**	**0,013**	**−0,008**	**−0,006**	**−0,006**	**0,005**	**0,002**	**0,004**
	T-statistic	0,324	−0,695	−0,599	−0,878	1,787	0,137	0,421
	Significance	Insign.	Insign.	Insign.	Insign.	*	Insign.	Insign.
(1,5)	**CAAR**	**0,014**	**−0,001**	**−0,009**	**−0,007**	**0,008**	**0,001**	**0,001**
	T-statistic	0,449	−0,082	−0,607	−1,119	2,384	0,057	0,148
	Significance	Insign.	Insign.	Insign.	Insign.	**	Insign.	Insign.
(-3,-3)	**CAAR**	**0,000**	**0,005**	**0,004**	**−0,005**	**−0,001**	**−0,001**	**0,000**
	T-statistic	0,007	0,293	0,235	−0,665	−0,182	−0,050	0,017
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.	Insign.
(-4,4)	**CAAR**	**0,032**	**0,012**	**−0,016**	**0,010**	**0,011**	**−0,001**	**0,015**
	T-statistic	0,765	0,656	−0,811	1,213	2,641	−0,040	1,412
	Significance	Insign.	Insign.	Insign.	Insign.	***	Insign.	Insign.

	Company	Robert Half International Inc.	BorgWarner Inc.	Kimco Realty Corp.	PORTFOLIO (VW)	PORTFOLIO (EW)
	CAAR	**0,011**	**0,018**	**−0,017**	**0,012**	**0,011**
(-5,5)	T-statistic	1,054	1,328	−2,544	7,051	9,279
	Significance	Insign.	Insign.	**	***	***
	CAAR	**0,012**	**0,015**	**−0,010**	**0,013**	**0,011**
(-5,-1)	T-statistic	0,772	1,007	−1,299	6,305	8,193
	Significance	Insign.	Insign.	Insign.	***	***
	CAAR	**0,008**	**0,010**	**−0,005**	**0,008**	**0,007**
(-3,-1)	T-statistic	1,232	1,321	−1,197	8,191	10,902
	Significance	Insign.	Insign.	Insign.	***	***
	CAAR	**0,002**	**0,015**	**−0,010**	**0,000**	**0,000**
(0,3)	T-statistic	0,234	1,728	−2,285	−0,206	−0,237
	Significance	Insign.	*	**	Insign.	Insign.
	CAAR	**0,000**	**0,002**	**−0,007**	**−0,001**	**−0,001**
(0,5)	T-statistic	−0,020	0,242	−1,336	−0,663	−0,928
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**−0,001**	**0,009**	**−0,008**	**0,001**	**0,001**
(-1,1)	T-statistic	−0,158	1,183	−1,984	0,759	1,358
	Significance	Insign.	Insign.	**	Insign.	Insign.
	CAAR	**0,005**	**0,010**	**−0,012**	**−0,001**	**0,000**
(1,3)	T-statistic	0,158	1,051	−2,677	−0,679	−0,682
	Significance	Insign.	Insign.	***	Insign.	Insign.
	CAAR	**0,003**	**−0,002**	**−0,009**	**−0,001**	**−0,001**
(1,5)	T-statistic	0,441	−0,196	−1,901	−1,024	−0,906
	Significance	Insign.	Insign.	*	Insign.	Insign.
	CAAR	**0,006**	**0,000**	**0,001**	**0,000**	**0,000**
(-3,-3)	T-statistic	0,657	−0,014	0,116	−0,203	0,437
	Significance	Insign.	Insign.	Insign.	Insign.	Insign.
	CAAR	**0,010**	**0,022**	**−0,015**	**0,011**	**0,009**
(-4,4)	T-statistic	0,981	1,840	−2,480	6,907	8,831
	Significance	Insign.	*	**	***	***

This table reports the cumulative average abnormal return (CAAR) for tweets with positive Trump sentiment for each of the 24 sample securities and the two portfolios in our study. The CAAR is aggregated across time, but not across securities due to total clustering (MacKinlay, 1997). Fama and French's (2015) five-factor model is employed as our normal performance measure. The sample period is 08.11.16 - 31.12.19. The first event window presented, (-5,5), represents the entire event window. The other windows are smaller intervals either before, during, or after the event. The T-statistic is found on the second line, below each associated CAAR. On the third line, ***, **, and * represent a significance level of 1%, 5%, and 10%, respectively. “Insign.” indicates that the CAAR is insignificant.

Table 11: Plot of cumulative average abnormal return (CAAR) for each security or portfolio





This table illustrates the plotted cumulative average abnormal return (CAAR) for each security or portfolio in the event window. The blue line illustrates the CAAR for positive tweets, whereas the red line illustrates the CAAR for negative tweets. The CAAR is found on the vertical axis, while the horisontal axis indicate the specific day in the event window from day -5 to day 5. The abnormal returns are calculated using Fama and French's (2015) five-factor model as normal return measure.

Table 12: AAR for equal-weighted sub-portfolios

	Eight largest companies		Eight medium companies		Eight smallest companies	
Day	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,002	−0,006	0,001	−0,001	0,003	−0,002
−4	0,003	−0,007	0,001	−0,001	0,002	0,001
−3	0,003	−0,002	0,000	−0,001	0,002	−0,001
−2	0,005	0,001	0,001	0,000	0,005	−0,002
−1	0,001	−0,002	0,001	−0,003	0,003	−0,004
0	0,001	−0,004	0,001	−0,001	−0,002	−0,003
1	−0,002	0,002	0,000	0,001	0,000	0,002
2	0,000	−0,001	0,000	−0,001	0,000	−0,001
3	−0,002	−0,001	0,001	−0,002	0,002	0,000
4	0,000	0,000	−0,001	0,000	0,001	0,000
5	0,000	−0,004	−0,001	0,000	−0,001	0,000

This table examines which securities create abnormal returns. The 24 sample securities are divided into three size-classes, each containing 8 securities. These portfolios are then equal-weighted. The table reports the average abnormal return (AAR) for positive and negative tweets for each sub-portfolio in the event window. The first column indicates the specific day in the event window relative to the event date (day 0).

Table 13: CAAR for equal-weighted sub-portfolios

	Eight largest companies		Eight medium companies		Eight smallest companies	
Day	Positive	Negative	Positive	Negative	Positive	Negative
−5	0,002	−0,006	0,001	−0,001	0,003	−0,002
−4	0,005	−0,013	0,002	−0,002	0,005	−0,001
−3	0,009	−0,015	0,001	−0,003	0,007	−0,002
−2	0,014	−0,014	0,003	−0,003	0,012	−0,004
−1	0,015	−0,016	0,004	−0,006	0,015	−0,008
0	0,016	−0,020	0,005	−0,007	0,013	−0,011
1	0,014	−0,018	0,005	−0,006	0,013	−0,009
2	0,014	−0,019	0,005	−0,007	0,013	−0,010
3	0,012	−0,019	0,006	−0,009	0,015	−0,010
4	0,012	−0,020	0,005	−0,009	0,016	−0,011
5	0,013	−0,024	0,004	−0,010	0,015	−0,011

This table reports the cumulative average abnormal return (CAAR) for positive and negative tweets for each sub- portfolio in the event window. The 24 sample securities are divided into three size-classes, each containing 8 securities. The portfolios are equal-weighted. CAAR is the cumulative sample average abnormal return from day -5 until each specified day in the event window. In the first column, days are denoted relative to the event date, which is zero (0).

Preliminary Thesis Report

- Trump Tweets' impact on financial returns -

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Ignacio Garcia de Olalla Lopez

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Source: Barrons, 2019 - Illustration by Robert Connolly.

Introduction

This preliminary thesis report concerns *President Donald Trump's tweets' impact on global financial markets*. Our goal for this research is to measure to which extent key presidential tweets affect global financial markets. The study will be conducted using an event analysis.

Donald J. Trump was elected as the United States' 45th President on November 8, 2016. One important distinction which separates Donald Trump from his predecessors is his widespread use of Twitter to **communicate with the public.** Moreover, Trump also has a strong focus on financial markets, and there is little doubt that investors now tries to take president trump's actions and tweets into consideration in their risk analysis. One investor, Dom Catrambone of Vol Shares, told Business Insider (2019) the following, concerning the impact of Trump's potential impeachment and the consequential effect of algorithmic trading on stock markets;

> One key element in today's trading environment is the advent of algorithmic trading. In this trading method, various terms from political and news coverage, such as 'Trump' and 'Impeachment' will automatically trigger trading signals, therefore adding non-fundamental reasons for a particular upswing or downturn in the markets (Dom Catrambone, 2019).

Non-financial news and information have the potential to affect global financial securities. Similarly, the Volatility Index (VIX), Gold prices, Crude Oil prices, S&P 500, Apple, Amazon and US treasury yields might all be impacted by presidential tweets. It is these abnormal effects or abnormal returns that will be attempted measured and further investigated in our thesis. More and more funds, investors and other asset managers are becoming increasingly algorithmic and data-driven. Hedge funds such as Renaissance Technologies, S.D Shaw, and perhaps more recently, XTX, have all demonstrated how one could utilize mathematical models and big data analysis to generate excess returns. Similarly, in our thesis, we aim to investigate how non-financial signals from the popular microblogging site Twitter can help forecast market movements. More specifically, we want to look at how certain presidential tweets, moods or sentiment can predict different securities and markets, as well as how it impacts general market volatility. Forbes asked Vladimir Signorelli, head of Bretton Woods Research, an investment research firm, who said the following about Twitter as an information tool; "Twitter has got to be one of the most undervalued online properties. It's quickly becoming a Bloomberg killer. Who needs to go to Bloomberg when you can go to Twitter" (Vladimir Signorelli, 2020).

So, how predictive are twitter feeds and sentiment on stock and other financial securities' returns? To investigate the phenomenon described above we aim to answer the following research questions:

Research Questions

(1) President Donald Trump's tweets impact US Stock returns.
(2) President Donald Trump's sentiment impacts US Stock returns.
(3) President Donald Trump's tweets correlate with volatility as measured by the VIX index.
(4) President Donald Trump's tweets impact gold prices.

Literature review

Both financial and non-financial information can move financial securities and markets in either direction. During especially the last years there has been an increasing interest in understanding how Donald Trump's rather unique method of communication with the public through Twitter, might affect global financial markets. JP Morgan for one conducted a study that led to the birth of the Volfefe Index. The name consists of the unknown word from one of Donald Trump's viral tweets "covfefe" (which is thought to be a misspelling of the word coverage) merged with the word volatility. This index mainly concerns the effect of presidential tweets on US bond yields. According to JP Morgan, there is substantial evidence suggesting that presidential tweets move US bond yields. Moreover, they also found that Trump usually has contrary opinions on American monetary policy than those by the Fed (Bloomberg, 2019). This study shows some similar characteristics to what we will attempt to measure and investigate. However, where JP Morgan focused on US treasury yields, our thesis focus on the broader stock and selected commodities markets. Another large investment bank, Bank of America Merrill Lynch, found the following relationship between trump's tweets and the stock market; "since 2016, days with more than 35 tweets (90 percentile) by Trump have seen negative returns (-9bp), whereas days with less than 5 tweets (10 percentile) have seen positive returns (+5bp) — statistically significant" (CNBC, 2019). In other words, there seems to be a correlation between the number of tweets in a day and stock market returns. When Trump tweets a lot there tend to be a slightly negative return, whereas when he tweets less there seems to be a slightly positive return. Although these are not thorough and well-acknowledged studies, they do, however, give an idea of the potential insight and value that can be drawn from unstructured twitter data.

Twitter as a predictive tool for forecasting future outcomes

Over the last decade, there have been conducted several studies on the explicit effect or predictive value of different social media on stock markets. One important study by Johan Bollen, Huina Mao and Xiao-Jun Zeng (2010) investigated how Twitter mood might help predict stock market returns. They utilized two sets of algorithms to classify and analyse people's sentiment on twitter feeds. The algorithms used were OpinionFinder and their own-developed algorithm Google Profile of Mood States (GPOMS), which measured moods in terms of 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy). After they had successfully classified the public sentiment using large twitter feeds, they applied Granger causality analysis and a Self-Organizing Fuzzy Neural Network to see if there was a correlation or predictive value between the public's mood and the returns of the Dow Jones Industrial Average (DJIA). The researchers found that certain dimensions had a strong predictive value, while others did not. Especially, the calm mood-dimension seemed to have a strong predictive value on the DJIA, providing similar price movements after 3 or 4 days.

A similar study was conducted by Sitaram Asur and Bernardo A. Huberman (2010), when they measured the predictability of chatter from Twitter by forecasting box-office revenues for movies in advance of their release. The researchers found that there was evidence suggesting that increased attention concerning a movie had a positive correlation with later rankings. Dhar and Chang (2007) also found similar evidence when conducting a study on how the volume of blog posts about an album is positively correlated with future sales. As these studies show, there might exist indicators in the public sentiment and activity on social media, which in turn can help forecast or predict future outcomes.

Conducting Twitter Sentiment Analysis

Twitter is a popular online microblogging site with millions of people sharing their opinions and views every day. This feature makes it a good source for detecting and performing sentiment analysis. In 2009 a group of researchers at Stanford University, Go, Bhayani and Huang, trained their machine learning model (Naive Bayes, Maximum Entropy, and support vector machines (SVM)) to structure and classify sentiment based on twitter feeds. Different corpora were first classified by emoticons to determine whether the tweet was positive or negative (neutral tweets were left out of this research, as this showed poor accuracy). The emoticons were later stripped-off, as especially the Maximum Entropy and SVM seem to put too much weight on these terms, which in turn hurt the accuracy of the algorithms. The researchers found that their machine learning techniques were able to identify sentiment with over 80% accuracy for all the three techniques applied. Much of this research was based on a previous research paper by Pang and Lee (2002), who used movie reviews as data. Comparatively, they achieved an accuracy of 70%. However, a study conducted by Pak and Paroubek (2010) found, using movie reviews as data, that standard machine learning techniques definitively outperform human-produced baselines. However, the three machine learning methods employed (Naive Bayes, maximum entropy classification, and support vector machines) do not perform as well on sentiment classification as on traditional topic-based categorization. These studies show that machine learning techniques can be applied to classify and structure sentiment in large data sets and that these techniques are proven superior compared to human-based sentiment classification. Moreover, they further cement the applicability of sources like Twitter for opinion mining and sentiment analysis.

In our thesis, we aim primarily to investigate whether presidential tweets correlate with the market or have any predictive value for selected indexes and securities. Consequently, we have chosen an event-study methodology to measure the impact of presidential tweets on the same and the following day. However, if possible and applicable, it would be valuable to investigate whether different presidential sentiments have an impact on stocks and other financial securities in addition to our primary study. This will be tested during the first part of the thesis project.

Research methodology

To conduct this research we plan to use event analysis, measuring abnormal returns on selected securities and indexes which correlates with key tweets from President Donald Trump.

To measure the correlation or to predict the impact of presidential tweets' financial securities' returns, we will use the procedure developed by MacKinlay (1997). MacKinlay explains that the initial step to successfully conduct an event analysis is to define the event(s) of interest and determine the period over which the securities involved in the incident shall be examined. In our case, by using an event analysis one can measure the abnormal returns originating from key presidential tweets within a short period after the publication. This period is known as the *event window*. It is normal to expand this period to multiple days, say, at least the day of interest and a day after. This is to capture the full effect of the event. Often, it is also useful to include a day before to the event, as the market might acquire information before the actual announcement or even forecast the event happening in advance. Thus, by including a day before the event one captures pre-event returns as well.

After having identified the event, it is necessary to develop some criteria for selection or inclusion in the study, as well as noting any biases that might occur during this selection. To capture the effect of the event, we are to measure if the event causes any abnormal returns. This follows from the simple formula below (for firm i and event date t):

$$AR_{it} = R_{it} - E(R_{it}|X_t) \qquad (1)$$

Explanation of variables

AR_{it} : Abnormal returns

R_{it} : Actual returns

$E(R_{it}|X_t)$: Normal return. Defined as the expected return without conditioning on the event taking place.

There are two common choices for modeling the normal return. These are the *constant mean return model* where the Xt is constant, and the *market model* where Xt is the market return. The constant mean model assumes constant returns over time, whereas the market model assumes a linear relationship between the market return and the security return. Other statistical models that one may apply are the factor or multifactor model. The market model is an example of a one-factor model, which follows from the formula:

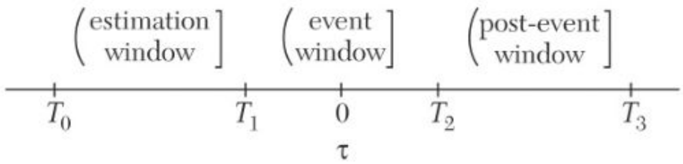
$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \qquad (2)$$

$$E(\varepsilon_{i,t} = 0)\,,\, var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon_i}$$

We will use t to index the returns in event time. $R_{i,t}$ and $R_{m,t}$ are the returns on security i and the market portfolio in period t. $\varepsilon_{i,t}$ is the zero mean disturbance term, and α_i, β_i and $\sigma^2_{\varepsilon_i}$ are parameters in the market model.

Additionally, there exist multifactor models that also include industry indexes, as well as the market. But the benefit of using multifactor models for event studies is limited as the marginal effect of adding factors is small and the reduction in the variance of the abnormal return is small. The reduction in the variance of the abnormal return is greatest when the sample firms included have a common characteristic, for example, common industry or market capitalization group (MacKinlay, 1997). In our thesis, we will apply the market return model or the multifactor model. The choice will be made after having conducted a preliminary test of applicability. Afterwards, the *estimation window* must be defined. This is done through measuring the securities' returns over a period *prior* (if representative and feasible) to the event, to estimate a parameter for normal returns. Typically, this window is set to 120 days. It is also typical for the estimation window and event-window not to overlap. This ensures that the normal returns are not affected by the event.

MacKinlay also proposes to include a third period known as the post-event window. Sometimes the post-event is included with the estimation window, to increase the robustness of the normal return measures. Below follows an illustration of how one might structure the different measurement windows in an event-study:



(MacKinlay, 1997)

$t = 0$ illustrates the event date. $t = T_0 + 1$ to $t = T_1$ represents the estimation window, $t = T_1 + 1$ to $t = T_2$ illustrates the event window and $t = T_2 + 1$ to $t = T_3$ shows the post-event window. Furthermore, $L_1 = T_1 - T_0$, $L_2 = T_2 - T_1$ and $L_3 = T_3 - T_2$.

In the next section, the market model will be used to explain the methodology, and how one should proceed to successfully measure and analyze the abnormal returns. The abnormal returns equal the difference between the actual return and the normal (expected) return. By inserting the market model into the abnormal return model, we get:

$$AR_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{m,t}) \tag{3}$$

The abnormal returns will follow a normal distribution under the null hypothesis which states that the event does not affect the returns:

$$AR_{i,t} \sim N(0, \sigma^2(AR_{i,t})) \tag{4}$$

Furthermore, the conditional mean will be zero and the conditional variance is defined as:

$$\sigma^2(AR_{i,t}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{m,t} - \widehat{\mu}_m)^2}{\widehat{\sigma}^2_m}\right] \tag{5}$$

This term is divided into parts. The first, $\sigma^2_{\varepsilon_i}$, is the variance from the error term in (2). The second part, $\frac{1}{L_1}\left[1+\frac{(R_{m,t}-\hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right]$, is additional variance due to the sampling error in α_i and β_i. As the estimation window increases, and if we assume that 120 days is large enough, the second component will approach zero as the sampling error of the parameters disappears. Thus, we get:

$$\sigma^2(AR_{i,t}) = \sigma^2_{\varepsilon_i} \tag{6}$$

To conclude the event of interest, MacKinley shows that the abnormal return observations must be aggregated. In our study, we will use aggregation both through time and across securities. Moreover, we will produce a sample of firms representative for US stock returns, within an industry market index such as S&P500, DJIA, or Nasdaq. The null hypothesis will be that Trump's Tweets have no impact on the aforementioned securities (see research questions). When we aggregate the events and observations we will be able to draw overall inferences for the events of interest.

Next follows a step-by-step calculation of the aggregated cumulative abnormal return model. The cumulative abnormal return is derived from the simple formula, which only considers a single security:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{7}$$

The variance of CAR_i is:

$$\sigma^2_i(t_1, t_2) = (t_2 - t_1 + 1)\sigma^2_{\varepsilon_i} \tag{8}$$

Whereas the distribution of the cumulative abnormal return under H_0 is:

$$CAR_i(t_1, t_2) \sim N(0, \sigma^2(t_1, t_2)) \tag{9}$$

From (3) we can use $AR_{i,t}$ to aggregate each securities' abnormal returns for each event period. Consequently, we can analyze the abnormal returns for any event period by using the estimates below. Given N events, the sample aggregated abnormal returns for period *t* is:

$$\overline{AR_t} = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{10}$$

And given that L_1 is large, the variance is:

$$var(\overline{AR_t}) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma^2_{\varepsilon_i} \quad (11)$$

Furthermore, by using the same approach as in (7), the average abnormal returns can be aggregated over the event window:

$$\overline{CAR}(t_1, t_2) = \sum_{t=t_1}^{t_2}\overline{AR_t} \quad (12)$$

$$var(\overline{CAR}\ (t_1, t_2)) = \sum_{t=t_1}^{t_2} var(\overline{AR_t}) \quad (13)$$

Correspondingly, by forming the CAR's security by security, it is possible to aggregate through time:

$$\overline{CAR}(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \quad (14)$$

$$var(\overline{CAR}(t_1, t_2)) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma^2_i(t_1, t_2) \quad (15)$$

To be able to set the covariance terms to zero, the assumption for the variance parameters is that the event window for the N securities does not overlap. One can conclude the cumulative abnormal returns using:

$$\overline{CAR}((t_1, t_2) \sim N\left[0, var(\overline{CAR}(t_1, t_2))\right] \quad (16)$$

to test the null hypothesis that the abnormal returns are zero.

As the true value of $\sigma^2_{\varepsilon_i}$ is unknown, we use an estimator to determine the variance of the abnormal returns as in (11). MacKinley shows that a suitable choice might be the usual sample variance measure of $\sigma^2_{\varepsilon_i}$ from the market model regression in the estimation window. The null hypothesis can be tested by using

$$\theta_1 = \frac{\overline{CAR}(t_1, t_2)}{var(\overline{CAR}(t_1, t_2))^{1/2}} \sim N(0, 1) \quad (17)$$

and this can be used to compute $var(\overline{AR_t})$ in (11).

The approach above is basic, and it is possible to make adjustments to it. An alternative is standardization, which can lead to more powerful tests according to James Patell (1976). It might be a case to look into if necessary.

As MacKinlay describes, there are also several biases and obstacles that one much takes into consideration when performing event-analysis. The first he describes relates to making *inferences with clustering*. The aggregated abnormal return model assumes that the event windows do not overlap across securities. This assumption allows for calculating the variance of sample cumulative abnormal returns without concern about the covariance across securities since they are zero. However, when they do overlap, the distributional results for the aggregated abnormal returns are no longer applicable. This can be solved in two ways; 1) The abnormal returns can be aggregated into a portfolio dated using event time and the security level analysis presented above can be applied to the whole portfolio. Or 2), analyse the abnormal returns without aggregation. Hence, this implies testing the null hypothesis of the event having no impact using unaggregated security by security data. This approach is most commonly used when there is an event on the same day for several firms. The regression is then conducted using a multivariate regression with the event date as dummies. (MacKinlay, 1997).

Lastly, Craig MacKinlay lists and explains some of the pitfalls and considerations one must take into account when performing event analysis. Usually in event analysis, one test a single null-hypothesis that the given event has no impact on the returns. However, in some cases, it might be interesting to test the null-hypothesis while allowing for a mean effect or changing variance. This is accomplished by using the cross-section of cumulative abnormal returns to form an estimator for testing the null-hypothesis. Other issues that one can encounter when doing event analysis are 1) *Defining sampling interval.* E.g., there is a substantial gain of using daily intervals in contrast to monthly intervals, as the power of the event will show a greater impact using more frequent intervals. 2) *Event date uncertainty* occurs when it is difficult to capture the exact moment of an event happening. One example is before company press releases. How certain can one be that none of the players in the market have got a hold of the information before the rest or before the actual announcement? The usual way to solve this is to expand the event window to, for instance, ± 1 day. 3) *Robustness.* The statistical analysis presented above builds on the assumption that returns are jointly normal and temporally independently and identically distributed. Thus, one must assume normality or else the results will be asymptotic. However, this is generally not a problem for event-studies "because for the test statistics the convergence to the asymptotic distributions is rather quick" (MacKinlay, 1997, p. 35). 4) *Other biases* concern the fact that e.g. using closing prices does not capture the actual volatility or the price movements of the securities. If the securities are passively or illiquid securities there might occur non- or thin trading patterns, which reduce the securities' beta (indicating a lower risk/volatility due to low trading volume). Lastly, implicitly in the calculation of the cumulative abnormal return, there might occur an "upward bias". The bias occurs as a result of observation to observation rebalancing to equal weights combined with transaction prices which can represent both the bid and the offer sides of the transactions recorded. In these cases, the bias can be eliminated by using cumulative abnormal returns considering only buy and hold strategies.

Above we have explained our planned methodology in great detail, as described by Craig MacKinlay (1997). Although, this is the main framework within which we will conduct our study, small alterations or changes might occur. This will be more clear-cut when we have extracted our data and performed some preliminary test results. Besides, our hypothesis' and research questions might also be subject to small changes, as our goal for the study is to measure the broad impact of President Donald Trump's tweets on the financial markets. There are perhaps some limitations within the event-study methodology which prevent us from measuring the impact in its entirety. This is partly because that the event-study methodology usually concerns firm-specific events, such as earnings announcements, credit ratings, etc. Besides, normally the firm or the sample of firms are tested in comparison to their respective industries, markets or indexes, whereas in our study we want to measure the impact on the market indexes themselves. Nonetheless, the outline of this study has several interesting aspects and crossroads, which all can be individually pursued and provide with valuable insight. As described above, the final outline, goal, and approach will be more clear after the first phase of our thesis.

Complementary research and its methodology

In this thesis, we will use event-analysis as our main research methodology. However, we will continuously look for other research methods that can help contribute to or complement our main study, if applicable. Different machine learning techniques such as Naive Bayesian, SVM or Maximum Entropy might be applied if feasible and achievable. Hidden Markov Models (HMM) or the Welch-Baum Algorithm, for instance, might be used to identify different unobservable states, in a transferable model. If possible, one could use stochastic models to predict or forecast influential presidential tweets. This follows under the assumption that Trump's tweets are random, but simultaneously, a result of the preceding tweet. The different methodologies presented above are meant to serve as suggestions and directions which all would add value to our research, either now or at a later stage. We'll gladly hand over the baton to other researchers who also find this topic interesting.

Data collection and analysis

Data will be downloaded from Twitter using web crawlers or other tools for extracting data from Twitter's open API. Besides, there is a web site dedicated to President Trump's tweets called www.trumptwitterarchive.com, where one can download the data for further modifications and cleaning. Afterwards, we will use Stata, R/R-studio and perhaps Python to perform statistical analysis and regressions. Furthermore, by using sentiment classification tools such as OpinionFinder or a tool similar to Google Profile of Mood States (Bollen et. al.) one can analyse Trump twitter feeds and see if there is a correlation between the returns of selected securities, indexes and presidential tweets. For financial data, this will be extracted by using primarily daily data from Yahoo! Finance.

Progress Plan

January: Data collection, classification and backtesting of research methodology and its overall suitability for this study.

February: Define models, adapt research methodology and run regressions.

March: Interpret results and further testing/modifications.

April: Describing and formulating results.

May: Include other potentially complementary research which add value to the main study.

June: Final discussion and conclusions, as well as suggestions for future research.

July 1: Deadline

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