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The effect of CEO tweets on the stock market activity

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ABSTRACT

This paper examines the effect of Twitter use on the stock market activity, such as volatility, return and trading volume. The sample contains data of S&P 500 companies and the tweets of their CEOs over the period of 2012 – 2017. Via time-series regression the effects of Twitter use, on stock risk, return and trading volume are estimated. The results show no consistent effects of Twitter use on the risk, denoted as volatility and unsystematic risk. There is a positive effect of tweeting on the return and a positive effect of tweeting of CEOs with a large audience on the trading volume. The tweets also show optimal information efficiency of the stock market. The sentiment of a tweet plays no role in explaining the effect on the stock market activity. The conclusion is that the effects of the tweets of the CEOs are direct, small and limited and do not explain the variation on the stock market activity well.

Keywords: CEO Twitter, stock market activity, information efficiency, sentiment, audience
JEL classifications: G11, G14, G41

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

1.1 Background

In the last decade social media has become one of the most important sources of big data. For instance, the social media platform Twitter has 330 million monthly active users in the first quarter of 2019 and roughly 500 million tweets per day (Twitter Inc., 2019), and Facebook even has 2,38 billion monthly active users in the first quarter of 2019 (Facebook, 2019). Social media has become the most important data source for businesses and investors (Fan and Gordon, 2014), and more and more companies see the value of social media for their investors relations Joyce (2013). This means that analysing social media data can be useful for businesses and investors in the context of the financial market. Analysing social media can also be used for various other purposes: Social media can predict sales and can be used for trend analysis (Fan and Gordon, 2014; Gundecha and Liu, 2012), it can predict crime (Mayer-Schönberger and Cukier, 2013), influence brand awareness and brand reputation (Montalvo, 2011), and improve the marketing and advertising of a company by using a social influencer that uses their products and promote their brands (Omand, Bartlett and Miller, 2012; Gundecha and Liu, 2012).

There is a lot of previous research on the topic of social media analysis, and in particular on the social media platform Twitter. Twitter is interesting and popular among researchers, because it is one of the most used social media platforms and it has a real-time nature. On Twitter good news, bad news, opinions and sentiments can be delivered to everyone across the world with only one click of the mouse within a second. This makes Twitter an important data source to analyse big data. Previous research is only limited to the sentiment of investors on the social media platforms, for example Mao, Wei, Wang and Liu (2012) only looked at daily number of tweets that mention certain stocks. In previous research there is evidence for a significant effect of twitter usage on the stock market returns and volume[1]. But what is missing is research on the impact of CEOs that use Twitter on the stock market activity. Meschke (2004) showed that statements of CEOs during interviews on television influence the stock market activity. So, in previous literature the link between CEO statements on Twitter and their effect on the stock market activity is still unexplored. This could possibly help explain the large variation of stock market returns that cannot be explained by risk factors, which is a hot research topic since the papers of Markowitz (1952, 1959). The relevance of the link between Twitter usage of CEOs and stock market activity is

[1] This will be discussed more in depth in the literature section.

shown by the recent case of the stock of Tesla and the tweets of its CEO Elon Musk. Elon Musk tweeted that he would take Tesla private and that the funding was secured. This resulted in a spike in the stock price of Tesla, followed by a huge drop in the stock price when it became clear that the funding was not secured. The SEC filed a lawsuit against Musk for falsely spreading information that influenced the stock price heavily, which resulted in a large decrease of 14% of the stock price (Kelleher, 2018). Following the lawsuit, they reached a settlement together in 2018 which resulted in an increase of 5.5% of the stock price (Carey and Vengattil, 2018). This example illustrated how much stock price volatility can be generated because of a single tweet of a CEO. However, to this day, it is allowed for executives to make announcements via Twitter, as long as the information is truthful and publicly disclosed. However, Twitter is a medium and informal. Executives can retweet or respond to certain messages and conversate with other Twitter users. This does not all contemplate with the rules of the SEC. The rules state now that company executives can use Twitter to spread key information about their company as long as it is in compliance with the Regulation Fair Disclosure of the SEC. This states that the information must be disclosed fair, truthfully and publicly available to all investors. But CEOs do not use Twitter just for disclosing company information, but also for their joy of interacting with an audience (e.g. see Elon Musks tweets). Which brings up the question if the rules of the SEC regarding the use of Twitter by executives needs to be updated? To answer this question, the effect of CEOs that use Twitter on the stock price needs to be examined. This leads to the research question of this paper: *What is the effect of Twitter usage of CEOs on the stock market?*

1.2 Hypotheses

To answer the research question five hypotheses are tested:

Hypothesis 1: The company stock has more risk when the CEO uses Twitter.

When a CEO tweets, it is expected to result in more price movements of the stock in comparison to a stock from which the CEO does not tweet. An important assumption is that all investors, current investors and potential new investors of the stock, follow the CEOs on Twitter and keep an eye on their timeline. When a CEO tweets, a part of the investors can interpret certain tweets as a potential signal about the stock price and company performance, but not all investors interpreted public information the same (Kandel and Pearson, 1995). This will result in more noise for the stock price, which means that the volatility will be higher and so on the risk of the stock will be higher. Antweiler and Frank (2004) found the same effect for the volatility of stocks that were mentioned and discussed on online message boards. Since the social media replaced the online message boards, the expectation is that the same effect will emerge. If this effect exists, then it could have large implications. In that case it would be better for companies to forbid their CEO to use Twitter, and it would be recommended for investors to take the Twitter use into account in their investment decision because it affects the risk of a stock.

Hypothesis 2A: The return for stocks are significantly different when the CEO uses Twitter.

When a CEO tweets, it is expected to result in a lower stock return or in a higher stock return in comparison to firms from which the CEO does not tweet. Previous literature provides support for a negative and a positive effect. The support for a negative effect is based on the paper of Fang and Peress (2009). Fang and Peress (2009) find evidence for a negative effect of media coverage on the stock return, media coverage underperforms compared to no media coverage. In this paper it is assumed that the exposure of investors to the tweets of a CEO, is a new type of media coverage. Therefore, the same effect could be expected in this paper. Another support for this expectation is the “investors recognition hypothesis” of Merton (1987). Merton (1987) states that in a market with incomplete information investors do not know all the available securities. Therefore, stocks that have low investor recognition need to compensate their investors with a higher return for being not fully diversified. Media coverage could improve the investors recognition for certain stocks, which leads to a lower return.

There is also support for a positive effect of the Twitter use. Twitter is not just a media platform to expose a company. Gaines-Ross (2013) mentioned that new CEOs can use social media to interact with their business relations, customers and even employees. He argues that this could improve the operations of a company. Additionally, Culnan et al. (2010) states that Twitter usage can increase business value, so this could in theory increase the stock price. Empirical evidence for this theory is provided by Elliot et al. (2018). Elliot et al. (2018) shows with experimental evidence that CEOs that use Twitter to bring company news, have a social bond and a form of trust with investors, leading to more willingness to invest from investors. Whether the effect of Twitter on the stock return will be positive or negative is hard to predict because of conflicting previous research, but the fact that Twitter can have a significant effect is clear.

Hypothesis 2B: The stock market incorporates the effect of tweets of CEOs directly in the stock price.

The second part of hypothesis 2 will test the market efficiency hypothesis, and in particular the information efficiency. As described in Malkiel & Fama (1970), the market efficiency represents how much off all available information is fully reflected in the securities prices. In the context of this paper, the second hypothesis will test if there is a lag in the reaction of the security prices to the tweets of the CEOs. The test will reveal how rapidly on average the stock prices incorporate Twitter information, which states the information efficiency. The expectation is that information shared via Twitter is efficiently incorporated in the stock prices and has a limited lagging effect. This is expected because Twitter can deliver the tweets to every follower within milliseconds, and the use of Twitter to retrieve information by investors is increasing (Alden, 2013). However, CEOs can tweet during or even at the end of the opening hours of the stock exchange, which means that a lag up to one day can be expected.

Hypothesis 3: The sentiment of a tweet has a positive relation with the stock return.

It is expected that a positive sentiment of a tweet from a CEO will result in a positive effect on the return. Also, the expectation is that a negative sentiment of a tweet impacts the results negatively. This expectation is supported by findings in prior research (Bollen, Mao and Zeng, 2011; Mittal and Goel, 2012; Rao and Srivastava, 2012; Oliveira, Cortez and Areal ,2017). Prior research finds evidence regarding the effect of sentiment of tweets that mention certain stocks and/or indices and their stock price. Positive sentiment results in a higher stock price and negative sentiment in a lower stock price. In this paper it is expected that the sentiment of the tweet of the CEO is also an important signal for investors, since the CEO is often the face of a company.

Hypothesis 4: A larger audience on Twitter increases the relation of a tweet on the stock return positively.

This hypothesis states that an effect of a tweet on the stock return is moderated by the amount of exposure the tweet has. So, the more investors that receive the signal of the tweet, the larger the effect on the stock return will be of the tweet. It is already proven by Blankespoor et al. (2014) that Twitter can reduce the information asymmetry of investors. So, if a tweet is viewed by enough investors, then it can have an impact on the capital allocation on the stock market. This raises the expectation that CEOs that have a lot of followers on Twitter, do impact their stock price more than CEOs that have a smaller audience. Although this hypothesis is intuitive and seems logical, it is not yet proven that a larger Twitter audience has a bigger impact on the stock market.

Hypothesis 5: The use of Twitter increases the trading volume on the stock market.

This hypothesis states that the trading volume will be higher on days where the CEO has tweeted. Similar results have been found when it comes to internet message boards, which are the predecessor of social media (Wysocki, 1998; Antweiler & Frank, 2004). Both papers state that an increase in the message board volume leads to an increase in trading volume. Sprenger et al. (2014) find the same relation between trading volume and message volume for the Twitter platform. Although these papers are more regarded to the investor's activity on the online message boards, the same could still apply to the activity of CEOs on Twitter. The theory, according to Cao et al. (2014), is that investors can conversate with each other and induce other 'side-lined investors' that see confirmation of their signal. The Twitter platform can be used to publish information for CEOs and to conversate with investors, so the theory of Cao et al. (2014) could still lead to an increase in trading volume after the CEO tweets, since Twitter is an open and public platform that 'side-lined investors' can use.

The sample of this paper consists of companies from the S&P 500, that are studied in the period of 2012 until 2017. All tweets from publicly available Twitter accounts of the active CEOs in the sample period are gathered and studied. The dataset consists of daily company data such as returns, trading volume and is matched with the tweets of the corresponding company and day. The main test method in this paper is the time-series regression, considering the data set contains panel data. The tests of the hypotheses will be via interpreting the coefficients of the time-series fixed effect regressions, which controls for firm fixed effects and time fixed effects. There are two different measurements for risk, volatility and unsystematic risk, which are both measured for three different time frequencies, week, month and year. The unsystematic risk is the standard deviation of the residuals of three different models, CAPM model, Banz model (Banz, 1981) and the three-factor model (Fama & French, 1993). Next, the information efficiency will be tested with lag variables of tweets, which shows if there is a delayed effect in the adjustment of stock prices. Lastly, the sentiment of a tweet is classified as negative, neutral and positive, which makes it perfect for a sentiment analysis via time-series regressions.

The main results of this paper are as follows. There is no clear and significant effect of the use of Twitter on the risk of a stock. Both measurements for risk, volatility and unsystematic risk, show insignificant coefficients and in some model's small significant negative coefficients. Since the results are mostly insignificant or have a very small significant coefficient, it can be concluded that the use of Twitter has no effect on the risk of a stock.

However, there is an indication that there might be a negative effect on the risk, which is so far not explained in previous literature. Tweeting does have a positive effect on the return on the same day. Tweeting is also perfectly information efficient since the reaction on the stock return can only be seen on the same day and not on the following days. So, the stock prices adjust rapidly to the tweets. The Granger causality tests indicate that tweets Granger-cause the higher returns. There are no significant results regarding the effect of the sentiment of a tweet on the stock return. The same is found for the size of the audience a CEO has on Twitter. The use of Twitter on average has no effect on the trading volume. The total exposure that a CEO has on Twitter, which is the number of tweets per day times the followers, positively affects the trading volume, however this needs to be interpreted with caution since the Granger causality test points towards a potential reverse causality bias. The sentiment of a tweet plays no role in the effect on trading volume of a stock. It is important to note that the explanatory power of all the relevant coefficients excluding the control variables is very low across all time-series regressions. So, the significant results should be interpreted with caution since it could be that tweeting of a CEO plays on average no significant role in explaining risk, return and trading volume.

This paper is structured as follows: In section 2 previous literature is reviewed and some key articles are discussed, to give a clear context for this paper. Section 3 contains a description of the data that is used in this in this paper. In section 4 the methodology is described that is used to generate the results. Section 5 and section 6 contains the presentation of the results and a conclusion.

CHAPTER 2 LITERATURE

2.1 Relevant literature

In 1936 John Maynard Keynes used the term “Animal spirits” in his book for the first time in the economic context. Since that time, researchers and economists are searching for the determinants of the wild price movements and volatility on the stock market, that cannot be explained by the fundamentals of the companies. Fama et al. (1969) is one of the first empirical studies that incorporated news in explaining events on the stock market, and in their paper specifically stock splits. Followed by this paper, Roll (1984) extrapolates this research with empirical research on the effect of news on the variation of security prices on the stock market. Roll (1984) discovered that only a small share of the variation of stock market returns could be explained by news on the orange juice market. Merton (1987) came up with a model of capital market equilibrium under incomplete information in his paper to try to explain the variation in the stock market returns. The key assumption in his model is investors only use securities for their optimal portfolios that they know about, in his paper he calls it investors recognition. Under this model further research can test if firm-specific media, that helps with a firm’s visibility and recognition, can lead to more market activity. Based on the research of Roll (1984), Cutler, Poterba, and Summers (1989) examined the relation between the variation of stock market returns and news coverage for the whole asset market instead of just one market. The authors also found little evidence that the determinant of news coverage could explain the variation of the stock market returns. However, Mitchell and Mulherin (1994) found evidence for a relation between news announcements and market activity, which includes trading volume and market returns. The authors note that the relation is not particular strong and that this confirms the difficulty of linking volume and volatility to measures of information. Another interesting finding came from Klibanoff, Lamont and Wizman (1996). They report that major news announcements, that affect the fundamentals of a company, will lead some investors, that normally lag behind, to update their believes and react more quickly to the change in fundamentals. This is evidence for the fact the news does have a significant effect on the stock market.

The studies of the previous paragraph are all using news articles or newspapers, like the New York Times, to examine the effect of news on the stock market. But from the late 1990s the internet was upcoming, which would lead to a whole new media platform on which news announcements were published and shared. Also, online discussion forums were established, where investors would discuss investment decisions and expectations. Tumarkin and Whitelaw (2001) explored the link between the online discussion forums and market activity in their paper. They concluded that there is no causal link between online discussion forums and stock returns and volume. In fact, they found the reverse, market information influenced the discussion boards. Related to this paper, Antweiler and Frank (2004) explored the relation between online stock message boards and the stock market activity. In contrast to Tumarkin and Whitelaw (2001), the authors find a significant relationship between the online message board activity and the volatility of the stock returns. Antweiler and Frank (2004) also report that disagreement on the online message boards leads to fewer trades in the subsequent days. With the introduction of the internet it is also easier to identify how many people an online news story reaches. Several studies found evidence for a relation between the unique visitors and/or pageviews and the stock prices value (Trueman et al. 2000; Demers and Lev 2001; Dewan et al. 2002). Another interesting finding came from Meschke (2004). Meschke (2004) found that stocks experience a strong run-up and reversal during the 11 days after CEO interviews on CNBC. This shows that investors also use television interviews and the vision of the CEO to determine their investments.

So, if media coverage has an impact on the stock price and volume, then companies can take advantage of this relation. Shiller (2000) was the first to argue that “enhanced business reporting leads to increased demand for stocks, just as advertisements for a consumer product make people more familiar with the product, remind them of the option to buy, and ultimately motivate them to buy.” To follow up this research, Grullon, Kanatas, and Weston (2004) provide evidence for the relation between advertising expenditures and demand for stocks. In their paper they show that the greater the advertising expenditures of a firm, the larger the number of individual and institutional investors the firm has for their common stock. Media coverage and news decrease the information asymmetry that investors have, especially for less know companies, and so on increase the liquidity of a firm (Easly & O’hara, 2004). In a similar context, Frieder and Subrahmanyam (2005) showed that individual investors prefer visible, brand name stocks. This means that individual investors exhibit a propensity towards firms with easily recognizable products. Also, visibility on the stock market itself matters to be recognized and acknowledged by investors. Kadlec and Mcconnel (1994) report that a firm has a significant increase in the number of shareholders when they are listed on the New York Stock Exchange, and additionally the stock experiences abnormal returns after the listing announcement. Foerster and Karolyi (1999) also report abnormal returns for non-US firms that get listed on the US stock exchanges.

More recent studies do find evidence for a significant effect of media coverage on trading activity. Fang and Peress (2009) showed that media coverage has a significant effect on the cross-section of stock returns. Stock with no media coverage significantly outperform stocks with media coverage in the U.S. Yu-lei, Die-feng and Cheng (2010) provided the same evidence for the Chinese stock market. Engelberg and Parssons (2011) studied the effect of different media coverages of the same information event. They conclude that local media coverage increases the local trading volume and influences both the buying and selling decisions. This finding is related to the home bias, that states that investors invest more in local stocks than foreign stocks (Grinblatt and Keloharju, 2001; Huberman, 2001; Benartzi, 2001). So local media strengthens the effect of the home bias for investors.

Since the last 10 years a new type of media has become the most important source of data for investors and businesses, the social media (Fan and Gordon, 2014). This development has led to a lot of new studies regarding the effect of social media on the stock market. The most interesting social media platform for researchers is Twitter, due to its fast growth and real time-nature. The social media is similar to other news outlets in the sense that it can also help with the information asymmetry of investors. Blankespoor et al. (2014) show that firms that use Twitter can decrease the information asymmetry and lead to an increase in the liquidity, if the firms are not covered much in the other news outlets. Mao, Wei, Wang and Liu (2012) investigated the effect of the daily number of tweets mentioning the S&P 500 on the stock indicators of the S&P 500. The authors find evidence that the Twitter data is correlated with the stock indicators for the S&P 500. Also, they found a predictive nature of the Twitter data, since the Twitter data could help predict whether the closing price would go up or down. Another interesting subject in the previous literature is the effect of the sentiment of the tweets, since Tetlock (2008) already showed that negative words in firm-specific news stories can forecast low firm earnings and returns. Rao and Srivastava (2012) examined the effect of the sentiment of the tweets on DIJA and NASDAQ-100 index. They show a high correlation between the stock price and Twitter sentiments in their paper and they validate that the price of the indices is affected by Twitter discussion in the short term. However, Ranco, Aleksovsi, Caldarelli and Grčar (2015) showed that there is not always a correlation between Twitter sentiment and the DIJA index. They found that there is only a significant correlation during peaks of Twitter volume, which coincides with for example quarterly announcements but also other less obvious events. Related to this research and in line with the findings of Mao, Wei, Wang and Liu (2012), Bollen, Mao and Zeng (2011) discovered that the Twitter sentiment helps the accuracy of the predictions of the DIJA index returns. Mittal and Goel (2012) have the same finding in their paper. Oliveira, Cortez and Areal (2017) confirmed the same finding for the S&P 500 index, since Twitter sentiment and volume predicts the S&P 500 return in their paper. Tabari et al. (2018) even show causality between the stocks and the sentiment of the tweets. However, not all prior research point to the fact that Twitter sentiment can predict the stock returns. Kuleshov (2011) and Lachanski & Pav (2017) both tried to replicate the results of Bollen, Mao and Zeng (2011), and concluded that the Twitter sentiment could not predict the DIJA index returns. An explanation for these conflicting results could be because of sample selection. Sul, Dennis and Yuan (2017) find evidence that the sentiment of tweets of people with a lot of followers basically operate as large media outlets. However, the impact of the sentiment of the tweets of people with less followers can be seen 10 to 20 days later. So, considering the number of followers in the data selection can be important when predicting the stock return.

In the paper of Luo, Zhang Duan (2013) there is an interesting comparison between the effect of social media on the stock prices, compared to the effect of conventional online consumer metrics on the stock price. As mentioned in a previous paragraph, around the year 2000 the metrics of online media were website visits or online searches (Trueman et al. 2000, Demers and Lev 2001, Dewan et al. 2002), and they were also correlated with the stock prices. Luo, Zhang Duan (2013) conclude in their paper that the social media metrics are better in predicting the stock return than the conventional online consumer metrics. Also, the social media have a shorter wear-in time in predicting the stock return. Sprenger et al. (2014) show another benefit of the social media platforms when it comes to event studies. In the paper they use Twitter to asses news events in real time and link them to investors' perceptions and the news sentiment. This approach solves the problem of identifying the exact event date and the news sentiment, which is important since different news sentiment leads to different stock market reactions (Schmitz, 2007).

Twitter can potentially have a different effect on retail investors compared to institutional investors. Hirschleifer et al. (2008) showed that retail investors are the ones that react the most after extreme earnings announcement. Next, Bhagwat and Burch (2014) suggest that the Twitter audience of companies largely consists of retail investors, and that the retail investors are the ones to respond the most to news published via Twitter. Although, retail investors often trade on a small scale, previous literature suggests that they can in fact influence the prices (Barber, Odean and Zhu, 2009).

CHAPTER 3 DATA

3.1 Data selection

The sample consists of all companies that were part of the S&P 500 between the period January 1, 2012 and December 31, 2017. There is no exclusion of companies based of bankruptcy or another reason that caused the company to be removed from the S&P 500, which is necessary to prevent the survivorship bias. There is a complete list provided by COMPUSTAT for this sample period. For the sample set it is necessary to search for every CEO that was in charge of one of the companies of the S&P 500 in the corresponding sample period. The names of all the CEOs were gathered through the website of Bloomberg and through announcements of new appointments and resignations in news articles or on the company website. Next, every CEO is checked to see if they have a Twitter account through the official website of Twitter. Then every CEO is followed on Twitter to see if their tweets are available to the public, since the SEC rules state that official announcements are only allowed via Twitter if its publicly available. The tweets of the CEOs were gathered via Twitter API with a custom-made Python script. Due to a limit of the Twitter API, only 2000 tweets per CEO could be extracted. This led to an exclusion of two CEOs and their companies, namely Marcel Oclaure of the Sprint corporation and Marc Benioff of Salesforce, because they both tweeted significantly more than 2000 times in the sample period. Because of this exclusion the magnitude of a possible effect could be underestimated, and the results should be interpreted with caution, since they both tweeted significantly more than the others and had the largest number of followers.

In order to compute the sentiment of every tweet, different values were assigned to every tweet. The tweets were classified as positive (+1), neutral (0) or negative (-1) based on the content of the message. These classifications are calculated with a Python script and using the TextBlob sentiment analysis. The TextBlob module has a build in sentiment analyser that is already trained on datasets of movie reviews, so it can identify positive, negative or neutral statements, which makes it the perfect tool for identifying the sentiment of a tweet.

To measure the impact of a tweet based on the size of the audience, data for the total number of followers and the total exposure are gathered. The total exposure a CEO has on Twitter is the total number of times a tweet is delivered to a timeline on a daily basis (so the amount of followers times the tweets per day).

The CRSP database was used to extract all the prices of every company that was part of the S&P 500 in the sample period. The remaining stock and company info, which includes the trade volume, market value and book-to-market ratio, is extracted through the COMPUSTAT database.

3.2 Data descriptives

The usage of Twitter is becoming more and more popular. This is also clearly visible in the data sample of this paper. Figure 1, see figure list at the end of the paper, shows that the total number of tweets of CEOs is increasing every year, and figure 2 shows that this goes hand in hand with the number of active Twitter accounts every year. Table 1 Panel A shows some additional Twitter descriptive statistics. The number of tweets per year illustrates how often the CEO uses Twitter to tweet. On average the CEOs tweet once every three days, the mean is 117, and there is even a CEO in the sample that tweeted almost four times a day in a specific year, namely 1301 in total. The number of Twitter accounts grew with a significant amount, from 16 in 2012 to 57 in 2017. The sentiment of tweets has an average value of 0.5, which indicates that most of the tweets are positive. Figure 3 confirms this suspicion and shows that more than half of the tweets are positive, and about a third neutral and only a small portion negative. Twitter is a platform to present yourself and for CEOs also their company, so it makes sense that they will express themselves largely positive and/or neutral and limit their negative statements. The number of followers illustrate a mean of 234,255, which is a skewed result because of a large outlier with 11.4 million followers. For this instance, the median is reported and shows that most CEOs have only around 11,017 followers. This low number of followers is largely driven by CEOs that rarely use Twitter, that leads to a low incentive to follow these CEOs. So, it is important to look at the active Twitter users of the sample.

Table 1: Data descriptive statistics

Panel A: Twitter statistics	Mean	Min	Max	Median
Number of tweets per year	117	1	1301	-
Number of twitter accounts per year	37	16	57	-
Sentiment of a tweet	0.507	0	1	1
Number of followers	234,255	78	11,457,154	11,017

Panel B: At least 1 tweet a year	Non-tweeting	Tweeting
Return	0.058%	0.069%
Volatility	0.0159	0.0159
B/M	0.455	0.295
Size	28,321,438	68,706,002
Volume	4,052,403	7,998,891
Share price	73.49	78.89

Notes: Number of tweets per year is based on the active Twitter users, which is denoted by a user that has tweeted at least once. The Sentiment of a tweet can be classified as positive = 1, neutral = 0, or negative = -1. The number of followers is an average over the whole sample period per Twitter user. Panel B group non-tweeting consists of companies from which the CEO has not tweeted that year. All variables of Panel B are yearly averages.

Table 1 Panel B illustrates a comparison between companies from which the CEO has tweeted at least once a year and CEOs that have not tweeted that year. Other time frequencies like weekly or monthly Twitter behaviour will also be explored and explained later in this paper. Panel B shows that tweeting companies have on average a larger return of about 0.011%, which is rather small. There is no clear difference in the volatility between the two. However, the B/M, size and volume have large differences. It looks like larger companies and low book-to-market ratio companies have an CEO that uses Twitter. The difference in volume is probably the result of the size difference between the two groups. So, it is important to take the size and book-to-market ratio into account when analysing the impact of CEO Twitter use. This means that both will be used as control variables in the regression analysis. Lastly, it seems that the share price is slightly lower for companies from which the CEO uses Twitter. The share price is relevant to control for a possible effect of retail investors, because they can potentially react more to tweets, as described in the literature section. Since it is difficult to identify what portion of shares of what company is traded by retail investors, it is assumed that they buy shares with a low price. The similarity in share price, and even a slightly higher share price for non-tweeting CEOs, suggests that the Twitter sample of CEOs is not biased towards the retail investors. Nonetheless, the share price is tested as a control variable to make the results more robust. The regression results did not change when the share price was added as a control, so the share price is left out of further regression analysis and results.

CHAPTER 4 METHODOLOGY

4.1 *Investors risk*

Risk for stock market investors can be measured in different ways. In this paper I start with a simple measure, the volatility of stock, and continue with a more complicated but specific risk measure, the unsystematic risk of a stock. Logically a stock with very volatile prices is considered riskier since investors have a chance to lose, or gain, money on their investment. The concept of unsystematic risk is introduced in the work of Markowitz (1952, 1959) in which he shows the two components of total risk of a stock portfolio. The two components of total risk he shows are the diversifiable risk, later known as unsystematic risk, and non-diversifiable risk, later known as systematic risk. Unsystematic risk is a firm-specific risk component that cannot be explained by risks such as the market fluctuations. It can be diversified away if the portfolio is large and diversified enough. However, investors and specifically U.S. investors do not diversify enough (Groetzmann and Kumar, 2005; Campbell, 2006). So, the unsystematic risk of a stock is an important risk factor for many investors to consider.

The volatility of a stock is based on daily data about the returns of a stock excluding the dividends. Then the standard deviation is taken for a week, month and a year of the daily data. This way I can compare the amount of Twitter that is used in a week, a month or a year to the volatility corresponding to this time frequency. I have chosen to include all three time frequencies so the results of this paper are more robust. Two control variables will be added to the time series regressions that can capture common risk factors, namely the market premium, size and book-to-market ratio (Fama & French, 1993).

To identify unsystematic risk, time series regressions are performed based on three different risk factor models from the previous literature and the residuals of these regressions are used to calculate the unsystematic risk. By performing these regressions, the systematic risk component of the total risk is eliminated, and the unsystematic risk component remains in the residual. This is the same approach as Marshall (2015) used to calculate the unsystematic risk of a single stock. Equation 1 shows the total risk σ_i that consists of a systematic component σ_m , which represents the market fluctuations, and an unsystematic component, or firm specific component σ_ε , which is the standard deviation of the residuals. To make sure that the results are robust, other systematic risk components will be added in the other two models. But the procedure of how the unsystematic risk component is calculated remains the same.

$$\sigma_i = b_i\sigma_m + \sigma_\varepsilon \tag{1}$$

The first and most basic model that I used is the CAPM model as described in Sharpe (1964) and Lintner (1965). This model contains a risk factor for the market premium return. The second model is an extension of the CAPM model because it adds a risk factor for the average size and is described in the paper of Banz (1981). The third and last model is the three-factor model of Fama and French (1993), that adds a risk factor for the size (SMB) and for the book-to-market value (HML). To make sure that the results are robust, three different time frequencies for time-series regressions with respect to the unsystematic risk and volatility are performed. I perform time series regressions for each stock and for each year, month and week[2].

$$R_{i\tau} - rf_\tau = a_{it} + b_{it}(R_{m\tau} - rf_\tau) + v_i + \varepsilon_{i\tau} \tag{1}$$

$$R_{i\tau} - rf_\tau = a_{it} + b_{it}(R_{m\tau} - rf_\tau) + \gamma_{it}[(\phi_{i\tau} - \phi_{m\tau})/\phi_{m\tau}] + v_i + \varepsilon_{i\tau} \tag{2}$$

$$R_{i\tau} - rf_\tau = a_{it} + b_{it}(R_{m\tau} - rf_\tau) + s_{it}SMB_\tau + h_{it}HML_\tau + v_i + \varepsilon_{i\tau} \tag{3}$$

τ is the subscript for the day and t is the subscript for week or month or year, depending on what time frequency is used in that specific time-series regression. As mentioned, all three time frequencies are tested. The coefficients b_i, γ_i, s_i and h_i are the factor loadings. v_i represent the fixed effect estimator. Fixed effects are used in these time series regressions to make sure that the within-group variation over time is accurate, and control for firm fixed effects and time fixed effects. Equation (1) shows the CAPM model with the excess return on the left-hand side and the market premium factor on the right-hand side. Equation (2) shows the model of Banz (1981), in which ϕ_i denotes the market value of security i and ϕ_m denotes the average market value. Equation (3) represents the three-factor model of Fama and French (1993), which includes the size premium (SMB) and value premium (HML).

4.2 Twitter

4.2.1 Hypothesis 1

Tweets need to be matched to the correct trading day, since tweets can be sent every day of the week and every minute of the day. First, all tweets in non-trading days are matched to

[2] The time series regression for each stock and for each month is similar to the procedure of French, Schwert & Stambaugh (1987) and Fu (2009)

the next trading day, in which logically the first market response to that tweet can occur. Secondly, tweets outside the opening hours of the NYSE are matched with the same trading day if the tweet was before opening hours and are matched with the next trading day if the tweet occurred after the opening hours. Lastly, if a CEO with a Twitter account is succeeded by his successor in the sample period, then all his tweets after he retired are left out this sample. It could be the case that these tweets still have influence, but this is hard to predict and is probably firm specific. So, in this paper it is assumed that these tweets won't have any influence after the official retirement.

In the regression analysis for the first hypothesis, which states that the company stock has more risk when the CEO uses Twitter, the use of Twitter is regressed on the volatility and unsystematic risk, see equation (5) and (6).

$$\sigma_{it} = a_{it} + b_{it}TWITTER + \varepsilon_{it} \quad (5)$$
$$\sigma_{it}^{\varepsilon} = a_{it} + b_{it}TWITTER + \varepsilon_{it} \quad (6)$$

t denotes week, month or year and as already mentioned all three regression will be performed. $\sigma_{it}^{\varepsilon}$ is the unsystematic risk, or in other words the standard deviation of the residuals of the risk factor models. The dummy for the use of Twitter, TWITTER, is 1 of the CEO has tweeted at least once, and 0 if he has not tweeted. Simply having a Twitter account is not analysed in this paper since having a Twitter account does not sent a signal, only tweeting does. This difference is important because some CEOs have a Twitter account but have never or almost never tweeted which often corresponds with a low number of followers.
First hypothesis test:

$$H_0: b_{it} > 0$$

To further explore the effect of tweeting, the frequency of tweeting is analysed. As described in the dataset, I had to exclude two CEOs that tweeted the most, which could underestimate a possible effect. CEOs that use Twitter daily have a larger potential effect compared to CEOs that used Twitter maybe once a year, if we assume that most of their tweets are interpreted as some sort of signal by investors. For this reason, four quartiles have been developed to distinct the frequent Twitter user from the non-frequent Twitter user. Quartiles have been developed for every time frequency, week, month and year, so they can be compared with the volatility and unsystematic risk variables. So, the 4th quartile for week includes the companies that have a CEO that is in the top 25% of the most frequent tweeters in that week. This means that the quartile that the company is in can change every week, since the quartiles are formed for every week based on the number of tweets. Important to note is that the quartiles are formed based on the weekly number of tweets of the entire sample set of companies that used Twitter. So, a company can tweet the most in a specific week compared to the other companies, but still not end up in the 4th quartile, if he did not tweet much relatively to the entire dataset. So, the 4th quartile consists weeks in which the number of tweets in absolute terms is the highest. The same procedure is applied to the monthly and yearly quartiles, which means that all three measures can differ from each other. The regression looks as follows:

$$\sigma_{it}^{\varepsilon} = a_{it} + b_{it}Q1 + c_{it}Q2 + d_{it}Q3 + e_{it}Q4 + v_i + x_{it}Controls + \varepsilon_{it} \tag{7}$$

So, for additional testing of hypothesis 1 the difference between the first and fourth quartile will be tested with a t-test mean comparison test:

$H_0: e_{it} > b_{it}$

4.2.2 Hypothesis 2

For the second hypothesis the relation between stock returns and Twitter use is explored. Twitter can be an informational channel for the stock market since the SEC changed the rules that allows companies and CEOs to reveal company info via Twitter. So, the equation to test the effect on the return looks as follows:

$$R_{i\tau} - rf_{\tau} = a_{it} + b_{it}Tweet + v_i + x_{it}Controls + \varepsilon_{i\tau} \tag{8}$$

The left-hand side represents the excess return. v_i denotes the fixed effect estimator and x_{it} all the coefficients for the control variables, which are the market premium, the size and the book-to-market ratio.

$H_0: e_{it} \neq b_{it}$

So, in addition to test for an effect on just the stock return, the market efficiency and specifically the information efficiency (Malkiel & Fama, 1970) will be tested. The information efficiency shows how fast the publication of new information is incorporated in the stock market. The information efficiency can be tested by introducing lag variables for the tweets. If the market is efficient then these lag variables should generate no significant results. When creating lag variables of every tweet, the non-trading days can generate some problems. To illustrate how the lag variables are created for the non-trading days, see Table 2. The problem is trading days just before the weekend since the lag variable should technically be a weekend day but that is a non-trading day. To solve this problem the lag variable is allocated to the next available trading day, which for a normal week is Monday. Although this approach is not perfect, it is the best available method to incorporate tweets on and around non-trading days.

Table 2: Tweet lag

Tweet day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Lag -1	Tuesday	Wednesday	Thursday	Friday	Monday	Monday	Monday
Lag -2	Wednesday	Thursday	Friday	Monday	Monday	Monday	Tuesday
Lag -3	Thursday	Friday	Monday	Monday	Monday	Tuesday	Wednesday

To measure the information efficiency, a simpler version of the approach of Hou and Moskowitz (2005) is used. The equation and the hypothesis test will look as follows:

$$R_{i\tau} - rf_{\tau} = a_{it} + b_{it}Tweet_t + \; c_{it}Tweet_{t-1} + d_{it}Tweet_{t-2} + e_{it}Tweet_{t-3} + f_{it}Tweet_{t-4} + g_{it}Tweet_{t-5} + v_i + x_{it}Controls + \varepsilon_{i\tau} \quad (9)$$

$$H_0: d_{it} = e_{it} = f_{it} = g_{it} = 0$$

This test states that apart from a direct effect and a one-day lag effect, there is no effect of tweets on the excess returns two, three, four or five days later.

Hypothesis 2 to 5 all include only time-series regressions. An issue that could arise is reverse causality since the regressions estimate a correlation between two variables. To overcome this problem, for every significant coefficient in the time-series regression a Granger causality test is performed[3]. This way the coefficient can be interpret as X Granger-causes Y, if the test is sufficient, instead of just a correlation.

4.2.3 Hypothesis 3

Hypothesis 3 tests the sentiment of a tweet. The sentiment of a tweet is classified with 1 for positive, -1 for negative and 0 for neutral. In this paper I do not look at tweets individually but rather at the effect of all tweets combined on a certain day, simply because I am using daily data rather than intra-day data. This poses the problem of multiple tweets in one day and their different classification of their sentiment. To solve this problem, I will calculate an average sentiment for every day that has more than one tweet. This means that the sentiment is classified on the interval [-1,1] instead of the three fixed values of -1, 0 and 1. In addition five lag variables of the sentiment will be created to adjust for a possible lack of

[3] For the procedure of a Granger causality test, see Granger (1969)

information efficiency. However, this approach eliminates the effect of multiple positive or negative tweets, since ten positive tweets have the same value, 1, as one positive tweet. For this reason, an extra robustness test is performed. An interaction effect between number of tweets and the average sentiment is calculated in the regression analysis to see if the same result holds. Another issue is the fact that neutral tweets, which are equal to 0, have the same value as no tweets, which also are equal to 0. So to disentangle these two and to make sure that the results are robust, three different dummy variables are created for mostly positive tweets, average sentiment [0.5, 1], neutral tweets (-0.5, 0.5), and mostly negative tweets [-1, -0.5]. These dummies are compared to the days of no tweets, so there is a clear effect of every twitter sentiment category. The basic sentiment and dummy regressions look as follows:

$$R_{i\tau} - rf_\tau = a_{it} + b_{it}Sentiment_t + c_{it}Sentiment_{t-1} + d_{it}Sentiment_{t-2} + e_{it}Sentiment_{t-3} + f_{it}Sentiment_{t-4} + g_{it}Sentiment_{t-5} + v_i + x_{it}Controls + \varepsilon_{i\tau} \quad (10)$$

$$R_{i\tau} - rf_\tau = a_{it} + \beta_{it}Posive + \gamma_{it}Neutral + \delta_{it}Negative \quad (11)$$

The hypothesis test for the basic regression, equation (10) states that the coefficients together have on average a significant and positive effect. Which means that positive tweets have a positive effect and negative tweets a negative effect.

$$H_0: b_{it} + c_{it} + d_{it} + e_{it} + f_{it} + g_{it} > 0$$

The test for the robustness check of the sentiments, equation (11) states that mostly positive tweets have a positive effect and mostly negative tweets have a negative effect.

$$H_0: \beta_{it} > 0 > \delta_{it}$$

4.2.4 Hypothesis 4

The fourth hypothesis denotes that a larger Twitter audience increases the relation between tweeting and the stock return. To measure this the average number of followers of a CEO is calculated over the sample period. This way there is an estimate on the average audience that every CEO had during their Twitter activity. The average number of followers times the number of tweets per day results in the impression, or the number of messages (tweets) a CEO has delivered to all the timelines of Twitter in total. This gives a good view of the total Twitter exposure of a CEO on a particular day. To test the hypothesis, two different regressions will be performed. The first regression contains the absolute number of the average followers times the number of tweets.

$$R_{i\tau} - rf_{\tau} = a_{it} + b_{it}\#Tweets + \ c_{it}Followers + \ d_{it}\#Tweets * Followers + v_i + x_{it}Controls + \varepsilon_{i\tau} \qquad (12)$$

$H_0: d_{it} > 0$

The second regression divides the average number of followers in four quartiles, in the same way as in hypothesis 1.

$$R_{i\tau} - rf_{\tau} = a_{it} + b_{it}Q1 + c_{it}Q2 + d_{it}Q3 + e_{it}Q4 + +v_i + x_{it}Controls + \varepsilon_{it} \qquad (13)$$

$H_0: e_{it} > b_{it}$

4.2.5 Hypothesis 5

The last hypothesis tests the effect of Twitter use on the trading activity of the stock market. Because there is daily data available for the trading volume, just as for the stock returns, the same regression analysis can be performed for this hypothesis. The trading volume is calculated as the following: $Trading\ volume = \frac{\text{Total traded shares}}{\text{Total shares outstanding}}$. As a robustness check another measure for trading volume is used: $Trading\ volume = \frac{(\text{Total traded shares}*\text{Share price})}{\text{Total shares outstanding}}$. This way there is a measure for the turnover, first measure, and for the dollar volume, second measure. The same regression that are already performed on the returns will also be performed with the trading volume as a dependent variable. The basic regression will look as follows:

$$Volume_{it} = a_{it} + b_{it}Tweet + v_i + x_{it}Controls + \varepsilon_{i\tau} \qquad (8)$$

$H_0: b_{it} > 0$

This test states that tweeting results in more trading volume. The other regressions have the number of tweets, impressions and the sentiment as the independent variables. These regressions are similar to equations (11) and (12) with the volume as the dependent variable instead of the excess returns.

CHAPTER 5 RESULTS

5.1 Effect Twitter use on risk

The first results are presented in Table 3 below. Table 3 shows the results of the effect of Twitter on the volatility of stocks for every week. The interpretation of the weekly regressions is the most important, since the effect of Twitter is short-term and is best captured in the weekly comparisons. To not rule out a long-term effect of Twitter, the results for monthly and yearly regressions are provided at the end of the paper in the Table section, see Table 4 and Table 5. Table 3 shows that without controls, (1) and (2), the use of Twitter has a significant negative effect on the volatility. However this is a rather small effect when we look at the coefficient and the low adjusted R^2. Also, the effect seems counterintuitive, since we would expect a larger volatility when Twitter is used. When the controls are added, (3), the significant effect of the use of Twitter disappears and is completely captured by the control variables. This is not in line with the effect found of other media coverage (Fang & Peress, 2009) and of the predecessor of Twitter, namely online message boards (Antweiler & Frank, 2004). The control variables show that smaller companies and companies with a higher book-to-market ratio have larger volatility, which is in line with the reasoning that these companies are considered riskier (Fama & French, 1993). The results for the monthly and yearly regression show a similar pattern as Table 3 (see Tables 4 and 5), because both have no significant effect of the use of Twitter when the controls are added. So, there is no significant effect of the use of Twitter on the stock volatility.

Table 3. Twitter effect on volatility - Weekly
Dependent variable: Volatility

	(1)	(2)	(3)
Twitter user	-0.0006***	-0.0006***	0.0000
	(0.0002)	(0.0002)	(0.0002)
Market Premium			0.0005
			(0.0027)
Size			-0.0000***
			(0.0000)
B/M			0.0022***
			(0.0000)
Fixed effects	no	yes	yes
Adjusted R^2	0.0000	0.0000	0.031

Notes: The dependent variable volatility is the standard deviation of the daily returns and is calculated for every week. The independent variable Twitter user is equal to 1 for a week if the CEO has tweeted at least once. The independent variables Market Premium, Size and B/M are a weekly average based on the daily data. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Next, the results of the effect of Twitter on the unsystematic risk component of the volatility is presented in Table 6. Again, the weekly regressions are presented below, and the monthly and yearly regressions are placed in the Table section (Table 7 and 8). Regression (1) shows that the use of Twitter has a negative effect on the unsystematic risk. This is again counterintuitive since there is no clear theory on why the use of Twitter should lower the unsystematic risk. On the contrary, it is expected that the use of Twitter creates extra and unnecessary risk, so as hypothesis 1 states you would expect a larger unsystematic risk. If we look at the other two models, we see that for the Banz model, (3), and the three-factor model, (5), there is again a negative effect but not significant at the 5% level. So only the unsystematic risk based on the CAPM model shows significant results. The monthly regression results, Table 7, show significant and negative coefficients for all three models, while the yearly regression results, Table 8, show negative but insignificant results for all models. What all models have in common is that they have low coefficients and a low adjusted R^2, which means that even the significant coefficients have a low and questionable explanatory power. So, to conclude the results are inconclusive, but there is an indication that a negative effect is present for the use of Twitter and the unsystematic risk.

To get a more detailed look in the effect of the frequency of the use of Twitter on the unsystematic risk, the quartiles of Twitter use are calculated. In Table 6 is only one significant result, which is the 4th quartile of the CAPM model, regression (2). This quartile is also significantly different from the lowest quartile, 1st quartile. This can be interpreted as the more Twitter a CEO uses, the lower the unsystematic risk. However, this result does not hold for the other two models, which do report a relative higher coefficient for the 4th quartile but no significant difference from 0 or from the 1st quartile. The monthly regressions in Table 7 do show a significant effect of the highest quartiles and report a significant difference between the highest and lowest quartile for all three models. However, the yearly regression in Table 8 shows no significant results for all quartiles and for every model. It is important to note that the significant coefficients of the results of these tables need to be interpreted with caution. Mainly because there is no explanation of why more tweeting would result in lower unsystematic risk. Also, the explanatory power of the variables is very low, since the reported adjusted R^2 and the coefficients are rather small. So, the results with regard to the frequency of Twitter use is inconclusive and hints to a potential negative effect of frequent Twitter users on the unsystematic risk. To conclude, the regression with volatility and the unsystematic risk show that there is no positive significant effect of Twitter use, which means that hypothesis 1 is rejected.

Table 6. Twitter effect on unsystematic risk - Weekly
Dependent variable: σ_ε

	CAPM		Banz model		Three factor model	
	(1)	(2)	(3)	(4)	(5)	(6)
Twitter user	-0.0005***		-0.0004		-0.0003*	
	(0.0002)		(0.0006)		(0.0002)	
1st quartile (low)		-0.0003		-0.0002		-0.0003
		(0.0002)		(0.0009)		(0.0002)
2nd quartile		-0.0003		-0.0001		-0.0004
		(0.0003)		(0.0009)		(0.0002)
3rd quartile		0.0000		-0.0006		-0.0008
		(0.0003)		(0.0009)		(0.0009)
4th quartile (high)		-0.0007**		-0.0014		-0.0004
		(0.0003)		(0.0009)		(0.0003)
Fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.0001	0.0001	0.0000	0.0003	0.0001	0.0001
T-statistic difference 4th - 1st		3.13***		1.48		1.57

Notes: The dependent variable σ_ε is the standard deviation of the residuals calculated for every week. The residuals are the result of the CAPM, Banz or three factor model, for the specific formula see equation (2), (3) and (4) in the methodology section. The independent variable Twitter user is equal to 1 for a week if the CEO has tweeted at least once. The quartiles are based on the number of tweets per week, in which the 4th quartile contains the highest number of tweets per week. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

5.2 *Information efficiency*

The results of hypothesis 2, which states that the use of Twitter has a negative effect on the stock return, are presented below in Table 9. The first regression, (1), shows no direct significant effect of tweeting on the stock return of the same day. The lag variables up to 5 days of lag are introduced in regression (2) and (3), which tests the information efficiency. Regression (2) shows a significant negative effect on the first lag variable, which indicates that the information efficiency may not be perfect and a lagged reaction on the stock market is present. To make sure that this result is robust, control variables are included in regression (3). What we see is a different result compared to regression (2). All the lagged variables have an insignificant coefficient and the normal variable of tweeting has a significant coefficient. This result indicates that the stock market has strong information efficiency when it comes to the informative signals of tweeting, which is in line with the theory that the stock market prices adjust rapidly to new information (Fama et al., 1969). The coefficient of tweeting is positive which means that tweeting results in a higher excess stock return for that day. To control for a reverse causality issue, Table 10 Panel A reports the Granger-causality test. The results confirm the expectation, namely tweets Granger-cause returns, and returns do not Granger-cause tweets. This result is also robust for up to three lags. The fact that tweets lead to higher returns is the opposite of the finding of Fang and Peress (2009) regarding the effect of media coverage. In fact the results seem to be in line with the theory of Culnan et al. (2010), who mentions that Twitter can create business value, or with Elliot et al. (2018), who mentions that Twitter forms a social bond and more trust with investors, especially with the smaller or retail investors. Another explanation for this could lie in the sentiment of the tweets. Figure 3 showed that most of the tweets are actually positive tweets and only a small portion are negative. So, if the stock market reacts positive on positive tweets and negative on negative tweets, then it could imply that on average the effect of tweeting will be positive. The results for these regressions are discussed in the next paragraph. What is missing in Table 9 is the weight of the number of tweets, since more tweets could have a larger impact on the return. The results for the test of the number of tweets on the return are provided in the Table section, see Table 11. This table shows that there is no significant effect for the number of tweets or for the lagged variables of the number of tweets. So, more tweets per day do not seem to generate higher returns. The results of Table 9 support hypothesis 2A, since there is a significant effect of tweeting on the stock return. The results also support hypothesis 2B since the stock prices reaction to tweets happen on the same day and not a day, or multiple days, later.

Table 9: Twitter effect on return
Dependent variable: Excess return

	(1)	(2)	(3)
Tweet	-0.02	0.03	0.04**
	(0.0002)	(0.0002)	(0.0002)
Tweet -1		-0.06***	-0.03
		(0.0002)	(0.0002)
Tweet -2		-0.03	0.00
		(0.0002)	(0.0000)
Tweet -3		-0.01	0.02
		(0.0002)	(0.0002)
Tweet -4		-0.03	0.01
		(0.0002)	(0.0002)
Tweet -5		-0.03	0.03
		(0.0002)	(0.0002)
Control variables	no	no	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.0000	0.0000	0.2185

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. Tweet is a dummy variable which is equal to 1 if there is a tweet from the CEO on that day. Tweet -1 is the lagged variable of one day of the dummy Tweet. The coefficients are denoted in percentages. The standard errors are in the parentheses and are robust. *Significant at the 0.1 level; **significant at the 0.05 level; ***significant at the 0.01 level.

One could argue that investors react differently to CEOs that tweet all the time compared to CEOs that tweet only a few times a month or year. The reason for this is that CEOs that tweet a lot might have less valuable information in their tweets. To test this, the yearly and monthly quartiles of the risk regressions are used, because they are based on the tweet activity of the CEOs. Table 12 Panel A shows that there are no significant effects for the interaction term of tweeting and the frequency of tweeting in that year. This means that the Twitter effect on returns of CEOs that tweeted the most in a particular year do not differ from CEOs that tweeted only a few times a year. Table 12 Panel B shows that this is also the case when we sort the quartiles based on the CEO Twitter activity of each month.

5.3 Sentiment

Next, the relation of the sentiment of the tweets and the stock return is analysed, to see if it can explain the results of Table 9. The third hypothesis stated that sentiment of a tweet has a positive effect on the return. Table 13 shows the results of the sentiment regressions. Regression (1) and (2) show no significant result for the average sentiment variable on the stock return of the same day. Regression (2) also shows that there is no delayed effect of the sentiment because all the lag variables are not significant, which is in line with the previous paragraph concerning the information efficiency. For the third regression the sentiment is split into three different groups and compared to the days where there is no tweeting. In this regression there is a significant coefficient for the neutral sentiment of a tweet. This can be interpreted as on average neutral tweets result in a higher return compared to no tweets. However, Table 10 Panel B shows that neutral tweets Granger-cause returns, but returns also Granger-cause neutral tweets. So, there is no clear causal effect of neutral tweets leading to higher returns. A mean comparison test between the three groups show that neutral tweets have significantly higher returns than positive tweets, but do not significantly differ from negative tweets. It could be that investors interpret neutral tweets as more of a credible message compared to overly positive tweets and react on average positively to this, however this is pure speculation since there is no data on the investors perspective in this paper and there exists some causality issues. These results are in contrast with the previous literature, e.g. Bollen et al. (2011), since there is no evidence of a positive effect of the sentiment of a tweet. As a robustness check, the effect of the number of tweets in combination with the sentiment is considered. Table 14 shows the interaction effect of sentiment and the number of tweets, since more positive tweets should be weighted more than just one positive tweet. The results of the table are in line with Table 13 because they both show no significant effect of the sentiment of a tweet. What can be concluded from this, is that hypothesis 3 is rejected, since the sentiment or the lag of the sentiment of a tweet does not play a significant role in explaining the stock returns. This also means that the positive results of tweets on the stock return, Table 9, cannot be explained by the sentiment of a tweet.

Table 13: Sentiment effect on return
Dependent variable: Excess return

	(1)	(2)	(3)
Sentiment	-0.06	0.02	
	(0.0002)	(0.0002)	
Sentiment -1		0.00	
		(0.0002)	
Sentiment -2		-0.02	
		(0.0002)	
Sentiment -3		0.02	
		(0.0002)	
Sentiment -4		-0.03	
		(0.0002)	
Sentiment -5		-0.00	
		(0.0002)	
Positive			0.02
			(0.0002)
Neutral			0.05**
			(0.0003)
Negative			0.05
			(0.0006)
Control variables	no	yes	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.0000	0.2185	0.2180

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. Sentiment is the average sentiment = sum of sentiment/total number of tweets, which is calculated for every day. Sentiment -1 is the lagged variable of one day of the average sentiment. The coefficients are denoted in percentages. The variables Positive, Neutral and Negative are dummy variables and are equal to 1 if the average of all tweets on a specific day are largely positive, neutral or negative. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

5.4 Audience

Table 15 shows the effect of the audience that a CEO has on Twitter on the relation of tweeting and the stock return. Hypothesis 4 states that the larger the audience that a CEO has on Twitter, the stronger the relation between tweeting and the stock return. In regression (1) of Table 15 there is no significant coefficient for the number of followers that a CEO has, which means that the audience does not seem to matter. Regression (2) has an interaction effect included between the number of followers and the number of tweets, which represents the total number of tweets that popped up on all timelines combined or in other words the total exposure the CEO had on Twitter on that day. Again, it is expected that more exposure on a particular day would lead to significant results but the coefficients of regression (2) are insignificant. The last regression, (3), has divided the number of followers in four different quartiles, to see if the same results as (1) and (2) hold. In regression (3) there is one significant, at the 5% level, and positive coefficient, namely for the third quartile. So, if the size of the audience is in the third quartile and there is at least one tweet, then the excess return is significantly higher in comparison to no tweets. The same would be expected for the fourth quartile, that contains the largest number of followers, but this coefficient is insignificant. Next, the coefficient of the third quartile is compared to the other quartiles with a mean comparison test. The result is that the third quartile does not significantly differ from the other quartiles. So, it cannot be concluded that size of the followers of the third quartile generates larger returns than the size of the number of followers of the other quartiles. Additionally, an interaction effect between the number of followers and tweets, as in regression (2), is tested for the four different quartiles. The results can be found in Table 16. The results show, in line with the other regressions, no significant effect of the total exposure of the four different quartiles. This indicates that there is no reduction of information asymmetry, or that reducing information asymmetry does not have a clear effect on the return, since the size of the audience does not matter. To conclude, hypothesis 4 is rejected, meaning that the audience of a CEO on Twitter does not have a significant impact on the returns when a CEO tweets.

Table 15: Audience effect on return
Dependent variable: Excess return

	(1)	(2)	(3)
# Tweets	0.00	-0.01	
	(0.0001)	(0.0001)	
# Followers	0.00	-0.00	
	(0.0000)	(0.0000)	
# Tweets *# Followers		0.00	
		(0.0000)	
Q1 - Followers			0.04
			(0.0004)
Q2 - Followers			0.01
			(0.0003)
Q3 - Followers			0.05**
			(0.0003)
Q4 - Followers			0.01
			(0.0003)
Control variables	yes	yes	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.2180	0.2180	0.2180

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. # Tweets is the number of tweets for a specific day. # Followers is the average number of followers over the whole sample period and is equal to 0 if there are no tweets on a specific day. Q1 – Followers is the first quartile of the number of followers, excluding the CEOs that do not have Twitter. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

5.5 Volume

The final results test the effect of Twitter on the trading volume. The fifth, and last, hypothesis states that Twitter use will significantly and positively impact the trading volume. The results are presented below in Table 17. The first regression shows that the effect of a tweet on the trading volume is positive but insignificant. This means that tweeting of a CEO does not create extra trading activity of investors. One could argue that there might be a delayed effect on the volume, just as the information efficiency test of the second hypothesis. So, additionally Table 18, located in the table section at the end of the paper, contains the lag variables of the tweets. This table shows that there is also no delayed significant effect because all the coefficients are not significant. So, we can rule out a delayed effect of the tweets on the trading volume.

In the second regression of Table 17 the number of followers and the total exposure are included, which is the interaction term between number of tweets and followers just as in hypothesis 4. The regression results show a positive and significant coefficient for the interaction term. The coefficient can be interpreted as the more total exposure a CEO has on Twitter on a particular day, the higher the trading activity for the company stock. So, in other words, if there are more tweets delivered to more timelines, the investors seem to react to these signals and start trading more of the stock. This could be because of the ‘side-lined investor’ theory of Cao et al. (2014). The ‘side-lined investors’ are investors that only follow conversations and they could be induced to participate in trading the stock by the tweets of CEOs or the public conversations on Twitter between the CEOs and investors or customers. However again, just as the regression results in the previous paragraphs, the overall adjusted R^2 of regressions (1), (2) and (3) is extremely low to none when the controls are removed. In addition, the Granger causality tests reported in Table 10 Panel C show that there might be some reverse causality issues, namely the test shows that volume Granger-causes total exposure and total exposure Granger-causes volume. Lastly, Table 19 reports the results of the different measure of volume. This table shows no significant results at the 5% level for all three regressions. This means that the significant result of regression (2) of Table 17 should be interpreted with caution.

The last regression, (3), tests if the sentiment of a tweet has an effect on the trading activity. The three dummy variables for positive, neutral and negative tweets show no significant coefficients, so the sentiment of a tweet does not matter when it comes to trading volume. The robustness check of Table 19 confirms these findings. To conclude, there is no general effect tweeting on the trading volume. However, it seems that if there are enough tweets and a large enough audience, or in other word a large exposure, then there is a possible positive effect of using Twitter on the trading volume, but this result is not robust. Overall, the results are insignificant and indicate no consistent effect of the use of Twitter on the trading volume, so hypothesis 5 is rejected.

Table 17: Twitter effect on volume
Dependent variable: Volume

	(1)	(2)	(3)
Tweet	0.1296	0.1228	
	(0.1336)	(0.1364)	
# Tweets	-0.0574	-0.0678	
	(0.0414)	(0.0418)	
# Followers		-0.0000	
		(0.0000)	
# Tweets *# Followers		0.0000**	
		(0.0000)	
Positive			0.1080
			(0.1229)
Neutral			-0.1190
			(0.1684)
Negative			-0.4169
			(0.4064)
Control variables	yes	yes	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.0327	0.0327	0.0327

Notes: The volume is specified as: $\frac{\text{Total traded shares}}{\text{Total shares outstanding}}$. Tweet is a dummy variable which is equal to 1 if there is a tweet from the CEO on that day. # Tweets is the number of tweets for a specific day. # Followers is the average number of followers over the whole sample period and is equal to 0 if there are no tweets on a specific day. The variables Positive, Neutral and Negative are dummy variables and are equal to 1 if the average of all tweets on a specific day are largely positive, neutral or negative. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

CHAPTER 6 CONCLUSION

6.1 Summary

In this paper the relation between the use of Twitters by CEOs and the stock risk, return and trading volume is explored. There is no consistent effect found that the Twitter use of CEOs raises the risk of a stock. In fact, there is a slight hint that it might reduce the risk. The tweets of CEOs have on average a positive effect on the return. This positive effect is seen on the same day as the tweet and shows no lagging effect, meaning that the tweets are perfectly information efficient. The sentiment of a tweet and the audience that a CEO has on Twitter both have no effect on the stock return. The sentiment of a tweet also has no effect on the trading volume of a stock. However, when the audience and the total number of tweets per day is considered, then there is a possible positive effect on the trading volume. So, when a CEO tweets more and has a larger audience, then it raises the trading volume.

6.2 Discussion

There are also some limitations in this paper. The first limitation is regarding the data selection. Due to the fact that there is a limit of 2000 tweets that can be extracted per Twitter CEO, the data sample could only consist of a few years and the two CEOs that tweeted the most and had the most followers had to be excluded of the sample. Also, only CEOs of S&P 500 companies were considered for the sample set, which means that some other CEOs that are quite popular in Twitter (e.g. Elon Musk), but not part of a S&P 500 company, were not included in the sample. Frederique Covington, international marketing director of Twitter, released a top 100 of most influential top executives based on the Twitter activity of the first half year of 2015, which is in the middle of the sample period of this paper (Dubois, 2016). In the top 20 of most influential executives, only four of the CEOs are also present in the data sample of this paper. So, it can be argued that there are a lot of influential CEOs missing in the data sample of this paper. This could all lead to an underestimation or overestimation of all the significant effects that were found in this paper. The most active Twitter users are the most interesting to study but as mentioned they are also the most difficult to study. So, if an alternative way is found to study this subsample, it is recommended to do so in further research. What is also missing in this paper is the categorization of the tweets of the CEOs. It would be helpful and interesting to categorize the tweets, so an effect of news related or personal tweets can be studied. The same applies to including the year 2018, 2019 and part of 2020 in further research since the popularity of CEOs that want use Twitter is rising just as the interest of investors in following CEOs on Twitter. So, if there is an effect present, it will be more pronounced in the last few years.

The overall consensus in this paper is that the explanatory power of the independent variables is very low. This raises the question if the significant results of this paper can really explain the dependent variables. However, it is important to note that previous literature established that stock returns are difficult to predict and have many variables that can explain it a portion of the variation. So, the effect that the independent variables have, which is rather small, could still be relevant in the real world. But, the effect cannot be fully proven in this paper. In addition to this, the results hint at a possible negative effect of Twitter use on the unsystematic risk. If this is actually the case, then that is very difficult to explain, since in practice the use of Twitter for CEOs is optional, and the tweet messages should just create extra noise in the stock prices which increases the unsystematic risk.

The characteristics of the shareholders of every company is another important factor that is missing in this paper and could be relevant for further research. As mentioned, retail investors could potentially react more to tweets than the institutional investors do. This effect is controlled via the share price in this paper, which is does capture some portion of the effect, but is not the optimal approach. If a distinction can be made between every type of shaleholder of every company, then the effect of Twitter can be tested for every group and the effect on the returns and trading volume can potentially be predicted more accurately. This means that the effect of Twitter can be larger for certain companies that have certain type of shareholders. So, it is recommended to explore this dimension in a Twitter analysis of the stock market in further research.

Finally, the methodology of this paper lacks the power to claim a causal effect. Time-series regressions can only show a correlation and no causation. Causation could be claimed when a difference-in-difference approach is used with a couple of assumptions. However, in this paper it was possible to apply such an approach. This is because there is particular point in time where a group of CEOs started using Twitter. Also, there were cases in which a CEO that used Twitter was succeeded by a CEO that did not use Twitter and vice versa. Another problem was that the CEOs that used Twitter did not use it consistently over time, in fact the periods in which they used it were inconsistent and frequencies in which they would use it was also inconsistent. This made it not possible to make a difference-in-difference analysis in this paper. It is recommended to explore the possibility of a difference-in-difference approach for further research. A possibility to overcome a part of the issue could be by selecting particular companies that have CEOs that started using Twitter around the same time and continue to use it for some years. However, one should be cautious for a possible sample selection bias.

6.3 Final remarks

To conclude, this paper sets the first step in exploring the average effect of Twitter use of CEOs on the stock market activity. On average the use of Twitter seems to have a limited effect on the stock market activity. There is only a small positive effect on the stock return and trading volume present but no evidence for extra risk. So, this paper does not provide evidence for the SEC to have a stricter policy regarding the average Twitter use of CEOs, since it does not produce extra noise for investors. However, the development of Twitter use among CEOs and investors is increasing so it is important to keep doing research in this field to see if an effect would also develop.

FIGURES

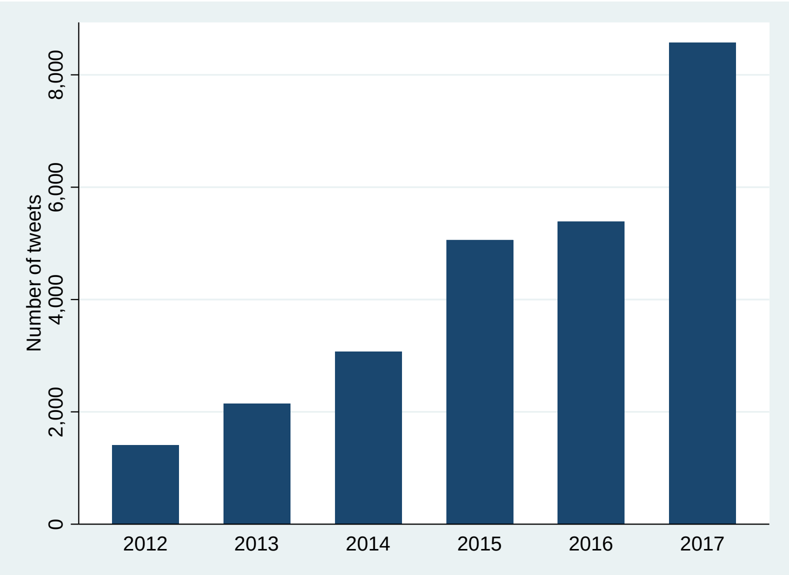

Figure 1: The development of the total number of tweets of the entire sample set over the sample period

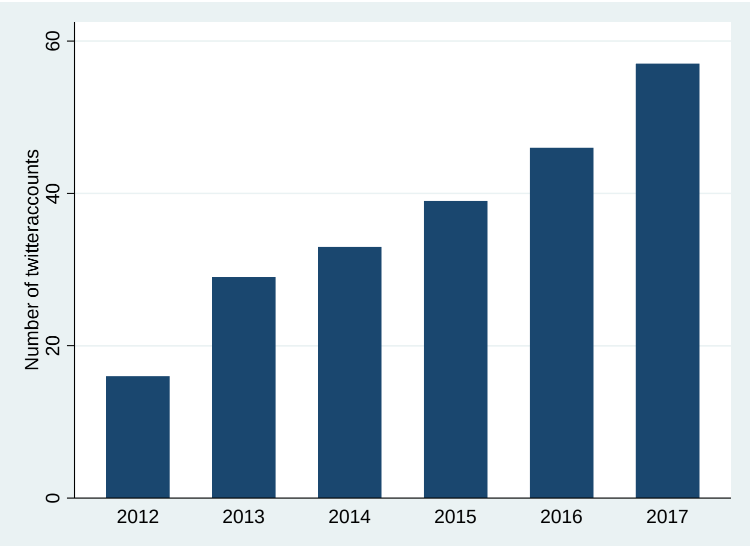

Figure 2: The development of the total number of Twitter accounts of the sample over the sample period

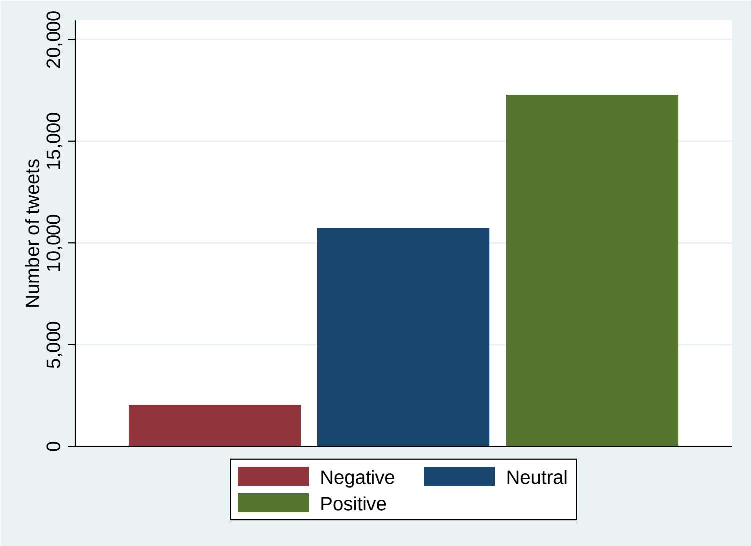

Figure 3: The sentiment distribution of negative, neutral and positive tweets of the total number of tweets of the sample.

TABLES

Table 4: Twitter effect on volatility - Monthly
Dependent variable: Volatility

	(1)	(2)	(3)
Twitter user	-0.0012****	-0.0012****	-0.0004
	(0.0002)	(0.0003)	(0.0003)
Market Premium			-0.0189***
			(0.0045)
Size			-0.0000***
			(0.0000)
B/M			0.0024***
			(0.0001)
Fixed effects	no	yes	yes
Adjusted R^2	0.0000	0.0000	0.0538

Notes: The dependent variable volatility is the standard deviation of the daily returns and is calculated for every month. The independent variable Twitter user is equal to 1 for a month if the CEO has tweeted at least once. The independent variables Market Premium, Size and B/M are a monthly average based on the daily data. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 5: Twitter effect on volatility - Yearly
Dependent variable: Volatility

	(1)	(2)	(3)
Twitter user	-0.0005	-0.0008	-0.0001
	(0.0005)	(0.0006)	(0.0006)
Market Premium			0.0029
			(0.0118)
Size			-0.0000***
			(0.0000)
B/M			0.0020***
			(0.0002)
Fixed effects	no	yes	yes
Adjusted R^2	0.0000	0.0000	0.0897

Notes: The dependent variable volatility is the standard deviation of the daily returns and is calculated for every year. The independent variable Twitter user is equal to 1 for a year if the CEO has tweeted at least once. The independent variables Market Premium, Size and B/M are a yearly average based on the daily data. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 7: Twitter effect on unsystematic risk - Monthly

Dependent variable: σ_ε

	CAPM		Banz model		Three factor model	
	(1)	(2)	(3)	(2)	(3)	(2)
Twitter user	-0.0009***		-0.0008***		-0.0008***	
	(0.0003)		(0.0002)		(0.0002)	
1st quartile (low)		-0.0002		-0.0002		-0.0003
		(0.0004)		(0.0009)		(0.0003)
2nd quartile		-0.0003		-0.0005		-0.0004
		(0.0004)		(0.0004)		(0.0004)
3rd quartile		-0.0008**		-0.0007*		-0.0008**
		(0.0004)		(0.0004)		(0.0009)
4th quartile (high)		-0.0012***		-0.0009**		-0.0010***
		(0.0004)		(0.0004)		(0.0004)
Fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.0000	0.0003	0.0000	0.0003	0.0000	0.0003
T-statistic difference 4th - 1st		4.49***		4.55***		4.47***

Notes: The dependent variable σ_ε is the standard deviation of the residuals calculated for every month. The residuals are the result of the CAPM, Banz or three factor model, for the specific formula see equation (2), (3) and (4) in the methodology section. The independent variable Twitter user is equal to 1 for a month if the CEO has tweeted at least once. The quartiles are based on the number of tweets per month, in which the 4th quartile contains the highest number of tweets per month. The standard errors are in the parentheses and are robust. *Significant at the 0.1 level; **significant at the 0.05 level; ***significant at the 0.01 level.

Table 8: Twitter effect on unsystematic risk - Yearly

Dependent variable: σ_ε

	CAPM		Banz model		Three factor model	
	(1)	(2)	(3)	(4)	(5)	(6)
Twitter user	-0.0004		-0.0004		-0.0004	
	(0.0006)		(0.0006)		(0.0006)	
1st quartile (low)		-0.0002		-0.0002		-0.0003
		(0.0009)		(0.0009)		(0.0009)
2nd quartile		-0.0000		-0.0001		-0.0001
		(0.0009)		(0.0009)		(0.0009)
3rd quartile		-0.0006		-0.0006		-0.0006
		(0.0009)		(0.0009)		(0.0009)
4th quartile (high)		-0.0014		-0.0014		-0.0014
		(0.0009)		(0.0009)		(0.0009)
Fixed effects	yes	yes	yes	yes	yes	yes
Adjusted R^2	0.0000	0.0003	0.0000	0.0003	0.0000	0.0003
T-statistic difference 4th - 1st		1.47		1.48		1.48

Notes: The dependent variable σ_ε is the standard deviation of the residuals calculated for every year. The residuals are the result of the CAPM, Banz or three factor model, for the specific formula see equation (2), (3) and (4) in the methodology section. The independent variable Twitter user is equal to 1 for a year if the CEO has tweeted at least once. The quartiles are based on the number of tweets per year, in which the 4th quartile contains the highest number of tweets per year. The standard errors are in the parentheses and are robust. *Significant at the 0.1 level; **significant at the 0.05 level; ***significant at the 0.01 level.

Table 10: Granger causality tests

Test	Lags	P-value
Panel A		
Return Granger-causes Tweets	1	0.12
Return Granger-causes Tweets	3	0.26
Tweets Granger-causes Return	1	0.00***
Tweets Granger-causes Return	3	0.00***
Panel B		
Return Granger-causes Neutral tweets	1	0.01***
Return Granger-causes Neutral tweets	3	0.03**
Neutral tweets Granger-causes Return	1	0.00***
Neutral tweets Granger-causes Return	3	0.02**
Panel C		
Volume Granger-causes Audience	1	0.00***
Volume Granger-causes Audience	3	0.00***
Audience Granger-causes Volume	1	0.00***
Audience Granger-causes Volume	3	0.08*

Notes: The null hypothesis states that Return does no Granger-cause Tweets, and the corresponding p-value shows if this null hypothesis can be rejected or not. If rejected, then the alternative hypothesis, Return does Granger-cause Tweets, is accepted. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level

Table 11: # Tweet effect on return
Dependent variable: Excess return

	(1)	(2)	(3)
# Tweet	-0.01	0.01	0.01
	(0.0001)	(0.0001)	(0.0000)
# Tweet -1		-0.01**	-0.01
		(0.0001)	(0.0001)
# Tweet -2		-0.00	0.00
		(0.0001)	(0.0001)
# Tweet -3		-0.00	0.02
		(0.0001)	(0.0001)
# Tweet -4		-0.01	-0.01
		(0.0001)	(0.0001)
# Tweet -5		-0.00	0.03
		(0.0001)	(0.0001)
Control variables	no	no	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.0000	0.0000	0.2185

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. # Tweet is a variable that represents the total number of tweets of a CEO on a specific day. # Tweet -1 is the lagged variable of one day of the # Tweet. The coefficients are denoted in percentages. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 12: Effect Twitter use frequency on return

Dependent variable: Excess return

	(1)	(2)
Panel A: Yearly quartiles		
1st quartile (low) * tweet	-0.0005	
	(0.0017)	
2nd quartile * tweet	-0.0015	
	(0.0016)	
3rd quartile * tweet	-0.0009	
	(0.0016)	
4th quartile (high) * tweet	-0.0011	
	(0.0016)	
Panel B: Monthly quartiles		
1st quartile (low) * tweet		0.0012
		(0.0008)
2nd quartile * tweet		0.0001
		(0.0007)
3rd quartile * tweet		-0.0001
		(0.0006)
4th quartile (high) * tweet		0.0003
		(0.0006)
Control variables	yes	yes
Fixed effects	yes	yes
Adjusted R^2	0.2180	0.2180

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. The interaction terms between the dummy tweet and the quartiles. The quartiles are based on the number of tweets per year, in which the 4th quartile contains the highest number of tweets per year and the dummy tweet represents whether a CEO has tweeted on that day. The individual terms of the variables are left out of the table to limit the size of the table. The coefficients are denoted in percentages. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 14: Sentiment and # tweets effect on return
Dependent variable: Excess return

	(1)	(2)
Sentiment	-0.00	0.00
	(0.0003)	(0.0003)
Sentiment*tweets	0.01	0.01
	(0.0001)	(0.0001)
Sentiment*tweets -1		0.00
		(0.0001)
Sentiment*tweets -2		0.00
		(0.0001)
Sentiment*tweets -3		0.00
		(0.0001)
Sentiment*tweets -4		-0.01
		(0.0001)
Sentiment*tweets -5		0.00
		(0.0001)
Control variables	yes	yes
Fixed effects	yes	yes
Adjusted R^2	0.2180	0.2185

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. Sentiment is the average sentiment = sum of sentiment/total number of tweets, which is calculated for every day. Sentiment*tweets is the interaction effect of the average sentiment and the total number of tweets, which is calculated for every day. Sentiment*tweets -1 is the lagged variable of one day. The coefficients are denoted in percentages. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 16: Audience and # Tweets effect on return
Dependent variable: Excess return

	(1)
Q1 Followers	0.04
	(0.0005)
Q2 Followers	0.04
	(0.0005)
Q3 Followers	0.07*
	(0.0004)
Q4 Followers	-0.01
	(0.0004)
# Tweets	-0.00
	(0.0002)
Q2 - Followers*#Tweets	-0.02
	(0.0003)
Q3 - Followers*#Tweets	-0.00
	(0.0003)
Q4 - Followers*#Tweets	0.01
	(0.0002)
Control variables	yes
Fixed effects	yes
Adjusted R^2	0.2180

Notes: The excess return is specified as: $R_{i\tau} - rf_{\tau}$. Q1 – Followers is the first quartile of the number of followers, excluding the CEOs that do not have Twitter. # Tweets is the number of tweets for a specific day. Q1 - Followers*#Tweets is left out to correct for the multicollinearity problem. The standard errors are in the parentheses and are robust. ∗Significant at the 0.1 level; ∗∗significant at the 0.05 level; ∗∗∗significant at the 0.01 level.

Table 18: Twitter lag effect on volume
Dependent variable: Volume

	(1)
# Tweets	-0.0426
	(0.0417)
Tweet	0.1771
	(0.1381)
Tweet -1	-0.0064*
	(0.1149)
Tweet -2	-0.0202
	(0.1153)
Tweet -3	-0.0762
	(0.1152)
Tweet -4	0.0979
	(0.1148)
Tweet -5	-0.3077
	(0.1144)
Control variables	yes
Fixed effects	yes
Adjusted R^2	0.0329

Notes: The volume is specified as: $\frac{\text{Total trading volume}}{\text{Total shares outstanding}}$. Tweet is a dummy variable which is equal to 1 if there is a tweet from the CEO on that day. # Tweets is the number of tweets for a specific day. Tweet -1 is the lagged variable of one day of the dummy Tweet. The standard errors are in the parentheses and are robust. $*$Significant at the 0.1 level; $**$significant at the 0.05 level; $***$significant at the 0.01 level

Table 19: Twitter effect on dollar volume
Dependent variable: Volume

	(1)	(2)	(3)
Tweet	-11.28	18.31	
	(13.25)	(13.51)	
# Tweets	7.58*	-2.15	
	(4.11)	(4.15)	
# Followers		-0.00	
		(0.00)	
# Tweets *# Followers		0.00	
		(0.00)	
Positive			-9.85
			(12.20)
Neutral			-8.58
			(16.72)
Negative			-15.43
			(40.34)
Control variables	yes	yes	yes
Fixed effects	yes	yes	yes
Adjusted R^2	0.0327	0.0021	0.0021

Notes: The volume is specified as: $\frac{(\text{Total traded shares} * \text{Share price})}{\text{Total shares outstanding}}$. Tweet is a dummy variable which is equal to 1 if there is a tweet from the CEO on that day. # Tweets is the number of tweets for a specific day. # Followers is the average number of followers over the whole sample period and is equal to 0 if there are no tweets on a specific day. The variables Positive, Neutral and Negative are dummy variables and are equal to 1 if the average of all tweets on a specific day are largely positive, neutral or negative. The standard errors are in the parentheses and are robust. $*$Significant at the 0.1 level; $**$significant at the 0.05 level; $***$significant at the 0.01 level.

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APPENDIX

Table 19: Data sample non-tweeting companies

Company Name	Ticker Symbol	Company Name	Ticker Symbol
3M CO	MMM	AMGEN INC	AMGN
A E S CORP	AES	AMPHENOL CORP NEW	APH
A T & T INC	T	ANADARKO PETROLEUM CORP	APC
ABBOTT LABORATORIES	ABT	ANALOG DEVICES INC	ADI
ABBVIE INC	ABBV	ANDEAVOR	ANDV
ABERCROMBIE & FITCH CO	ANF	ANSYS INC	ANSS
ACCENTURE PLC IRELAND	ACN	ANTHEM INC	ANTM
ACUITY BRANDS INC	AYI	AON CORP	AON
ADIENT PLC	ADNT	AON PLC	AON
ADOBE SYSTEMS INC	ADBE	APACHE CORP	APA
ADTALEM GLOBAL EDUCATION INC	ATGE	APARTMENT INVESTMENT & MGMT CO	AIV
ADVANCE AUTO PARTS INC	AAP	APOLLO EDUCATION GROUP INC	APOL
ADVANSIX INC	ASIX	APOLLO GROUP INC	APOL
AFFILIATED MANAGERS GROUP INC	AMG	APPLIED MATERIALS INC	AMAT
AFLAC INC	AFL	APTIV PLC	APTV
AGILENT TECHNOLOGIES INC	A	ARCHER DANIELS MIDLAND CO	ADM
AIR PRODUCTS & CHEMICALS INC	APD	ARCONIC INC	ARNC
AIRGAS INC	ARG	ASSURANT INC	AIZ
ALASKA AIRGROUP INC	ALK	AUTOMATIC DATA PROCESSING INC	ADP
ALBEMARLE CORP	ALB	AUTOZONE INC	AZO
ALCOA CORP	AA	AVAGO TECHNOLOGIES LTD	AVGO
ALCOA INC	AA	AVALONBAY COMMUNITIES INC	AVB
ALEXANDRIA REAL EST EQUITIES INC	ARE	AVERY DENNISON CORP	AVY
ALEXION PHARMACEUTICALS INC	ALXN	AVON PRODUCTS INC	AVP
ALIGN TECHNOLOGY INC	ALGN	B B & T CORP	BBT
ALLEGHENY TECHNOLOGIES	ATI	B M C SOFTWARE INC	BMC
ALLEGION PLC	ALLE	BAKER HUGHES INC	BHI
ALLERGAN INC	AGN	BALL CORP	BLL
ALLERGAN PLC	AGN	BANK OF AMERICA CORP	BAC
ALLIANCE DATA SYSTEMS CORP	ADS	BANK OF NEW YORK MELLON CORP	BK
ALLIANT ENERGY CORP	LNT	BARD C R INC	BCR
ALLSTATE CORP	ALL	BAXALTA INC	BXLT
ALPHABET INC	GOOGL	BAXTER INTERNATIONAL INC	BAX
ALTICE USA INC	ATUS	BEAM INC	BEAM
ALTRIA GROUP INC	MO	BECTON DICKINSON & CO	BDX
AMEREN CORP	AEE	BED BATH & BEYOND INC	BBBY
AMERICAN AIRLINES GROUP INC	AAL	BEMIS CO INC	BMS
AMERICAN ELECTRIC POWER CO INC	AEP	BEST BUY COMPANY INC	BBY
AMERICAN INTERNATIONAL GROUP INC	AIG	BIG LOTS INC	BIG
AMERICAN TOWER CORP NEW	AMT	BIOGEN IDEC INC	BIIB
AMERICAN WATER WORKS CO INC	AWK	BIOGEN INC	BIIB
AMERIPRISE FINANCIAL INC	AMP	BIOVERATIV INC	BIVV
AMERISOURCEBERGEN CORP	ABC	BLACKROCK INC	BLK
AMETEK INC NEW	AME	BOEING CO	BA

Company Name	Ticker Symbol	Company Name	Ticker Symbol
BORGWARNER INC	BWA	CITIGROUP INC	C
BOSTON PROPERTIES INC	BXP	CITIZENS FINANCIAL GROUP INC	CFG
BOSTON SCIENTIFIC CORP	BSX	CLEVELAND CLIFFS INC NEW	CLF
BRIGHTHOUSE FINANCIAL INC	BHF	CLIFFS NATURAL RESOURCES INC	CLF
BRISTOL MYERS SQUIBB CO	BMY	CLOROX CO	CLX
BROADCOM CORP	BRCM	COCA COLA CO	KO
BROADCOM LTD	AVGO	COGNIZANT TECHNOLOGY SOLS CORP	CTSH
C B O E GLOBAL MARKETS INC	CBOE	COLGATE PALMOLIVE CO	CL
C B O E HOLDINGS INC	CBOE	COLUMBIA PIPELINE GROUP INC	CPGX
C B S CORP NEW	CBS	COMCAST CORP NEW	CMCSA
C F INDUSTRIES HOLDINGS INC	CF	COMERICA INC	CMA
C M E GROUP INC	CME	CONAGRA BRANDS INC	CAG
C N X RESOURCES CORP	CNX	CONAGRA INC	CAG
C S R A INC	CSRA	CONCHO RESOURCES INC	CXO
C S X CORP	CSX	CONDUENT INC	CNDT
C V S CAREMARK CORP	CVS	CONOCOPHILLIPS	COP
C V S HEALTH CORP	CVS	CONSOL ENERGY INC	CNX
CABOT OIL & GAS CORP	COG	CONSOLIDATED EDISON INC	ED
CADENCE DESIGN SYSTEMS INC	CDNS	CONSTELLATION BRANDS INC	STZ
CAMERON INTERNATIONAL CORP	CAM	COOPER COMPANIES INC	COO
CAMPBELL SOUP CO	CPB	CORNING INC	GLW
CAPITAL ONE FINANCIAL CORP	COF	COSTCO WHOLESALE CORP NEW	COST
CARDINAL HEALTH INC	CAH	COTY INC	COTY
CAREFUSION CORP	CFN	COVENTRY HEALTH CARE INC	CVH
CARMAX INC	KMX	COVIDIEN PLC	COV
CATERPILLAR INC	CAT	CROWN CASTLE INTERNATIONAL CORP	CCI
CELGENE CORP	CELG	CROWN CASTLE INTL CORP NEW	CCI
CENTENE CORP DEL	CNC	CUMMINS INC	CMI
CENTERPOINT ENERGY INC	CNP	D R HORTON INC	DHI
CENTURYLINK INC	CTL	D T E ENERGY CO	DTE
CERNER CORP	CERN	D X C TECHNOLOGY CO	DXC
CH ROBINSON WORLDWIDE INC	CHRW	DANAHER CORP	DHR
CHARTER COMMUNICATIONS INC	CHTR	DARDEN RESTAURANTS INC	DRI
CHARTER COMMUNICATIONS INC NEW	CHTR	DAVITA HEALTHCARE PARTNERS INC	DVA
CHESAPEAKE ENERGY CORP	CHK	DAVITA INC	DVA
CHEVRON CORP NEW	CVX	DEAN FOODS CO NEW	DF
CHIPOTLE MEXICAN GRILL INC	CMG	DEERE & CO	DE
CHUBB CORP	CB	DELL INC	DELL
CHUBB LTD	CB	DELPHI AUTOMOTIVE PLC	DLPH
CHURCH & DWIGHT INC	CHD	DELPHI TECHNOLOGIES PLC	DLPH
CIGNA CORP	CI	DELTA AIR LINES INC	DAL
CIMAREX ENERGY CO	XEC	DENBURY RESOURCES INC	DNR
CINCINNATI FINANCIAL CORP	CINF	DENTSPLY INTERNATIONAL INC NEW	XRAY
CINTAS CORP	CTAS	DENTSPLY SIRONA INC	XRAY

Company Name	Ticker Symbol	Company Name	Ticker Symbol
DEVON ENERGY CORP NEW	DVN	EXPRESS SCRIPTS HOLDING CO	ESRX
DIAMOND OFFSHORE DRILLING INC	DO	EXPRESS SCRIPTS INC	ESRX
DIGITAL REALTY TRUST INC	DLR	EXTRA SPACE STORAGE INC	EXR
DISCOVER FINANCIAL SERVICES	DFS	EXXON MOBIL CORP	XOM
DISCOVERY COMMUNICATIONS INC	DISCA	F 5 NETWORKS INC	FFIV
DISH NETWORK CORPORATION	DISH	F M C CORP	FMC
DOLLAR GENERAL CORP NEW	DG	F M C TECHNOLOGIES INC	FIS
DOLLAR TREE INC	DLTR	FACEBOOK INC	FB
DOMINION ENERGY INC	D	FAMILY DOLLAR STORES INC	FDO
DOMINION RESOURCES INC VA NEW	D	FASTENAL COMPANY	FAST
DONNELLEY R R & SONS CO	RRD	FEDERAL REALTY INVESTMENT TRUST	FRT
DOVER CORP	DOV	FEDERATED INVESTORS INC PA	FII
DR PEPPER SNAPPLE GROUP INC	DPS	FEDEX CORP	FDX
DU PONT E I DE NEMOURS & CO	DD	FIDELITY NATIONAL INFO SVCS INC	FIS
DUKE ENERGY CORP NEW	DUK	FIFTH THIRD BANCORP	FITB
DUKE REALTY CORP	DRE	FIRST HORIZON NATIONAL CORP	FHN
E M C CORP MA	EMC	FIRST SOLAR INC	FSLR
E N S C O PLC	ESV	FIRSTENERGY CORP	FE
E N S C O PLC NEW	ESV	FLIR SYSTEMS INC	FLIR
E Q T CORP	EQT	FLOWSERVE CORP	FLS
E TRADE FINANCIAL CORP	ETFC	FLUOR CORP NEW	FLR
EASTMAN CHEMICAL CO	EMN	FOOT LOCKER INC	FL
EATON CORP	ETN	FORD MOTOR CO DEL	F
EATON CORP PLC	ETN	FOREST LABS INC	FRX
EDISON INTERNATIONAL	EIX	FORTIVE CORP	FTV
EDWARDS LIFESCIENCES CORP	EW	FORTUNE BRANDS HOME & SECUR INC	FBHS
ELECTRONIC ARTS INC	EA	FOSSIL GROUP INC	FOSL
EMERSON ELECTRIC CO	EMR	FOSSIL INC	FOSL
ENDO HEALTH SOLUTIONS INC	ENDP	FOUR CORNERS PROPERTY TRUST INC	FCPT
ENDO INTERNATIONAL PLC	ENDP	FRANKLIN RESOURCES INC	BEN
ENDO PHARMACEUTICALS HLDGS INC	ENDP	FREEPORT MCMORAN COPPER & GOLD	FCX
ENERGYSOLUTIONS INC	NSFDF	FREEPORT MCMORAN INC	FCX
ENTERGY CORP NEW	ETR	FRONTIER COMMUNICATIONS CORP	FTR
ENVISION HEALTHCARE CORP	EVHC	G G P INC	GGP
ENVISION HEALTHCARE HOLDINGS INC	EVHC	GALLAGHER ARTHUR J & CO	AJG
EOG RESOURCES INC	EOG	GAMESTOP CORP NEW	GME
EQUIFAX INC	EFX	GAP INC	GPS
EQUINIX INC	EQIX	GARMIN LTD	GRMN
EQUITY RESIDENTIAL	EQR	GARTNER INC	IT
ESSEX PROPERTY TRUST INC	ESS	GENERAL DYNAMICS CORP	GD
EVEREST RE GROUP LTD	RE	GENERAL GROWTH PPTYS INC NEW	GGP
EVERSOURCE ENERGY	ES	GENERAL MILLS INC	GIS
EXELON CORP	EXC	GENUINE PARTS CO	GPC
EXPEDITORS INTERNATIONAL WA INC	EXPD	GENWORTH FINANCIAL INC	GNW

Company Name	Ticker Symbol	Company Name	Ticker Symbol
GILEAD SCIENCES INC	GILD	IRON MOUNTAIN INC	IRM
GLOBAL PAYMENTS INC	GPN	IRON MOUNTAIN INC NEW	IRM
GOODYEAR TIRE & RUBBER CO	GT	J B G SMITH PROPERTIES	JBGS
GOOGLE INC	GOOGL	JABIL CIRCUIT INC	JBL
GRAHAM HOLDINGS CO	GHC	JABIL INC	JBL
GRAINGER W W INC	GWW	JACOBS ENGINEERING GROUP INC	JEC
H C A HEALTHCARE INC	HCA	JEFFERIES GROUP INC NEW	JEF
H C A HOLDINGS INC	HCA	JOHNSON & JOHNSON	JNJ
H C P INC	HCP	JOY GLOBAL INC	JOY
H P INC	HPQ	K L A TENCOR CORP	KLAC
HALLIBURTON COMPANY	HAL	KANSAS CITY SOUTHERN	KSU
HANESBRANDS INC	HBI	KELLOGG CO	K
HARLEY DAVIDSON INC	HOG	KEYCORP NEW	KEY
HARMAN INTL INDS INC NEW	HAR	KIMBERLY CLARK CORP	KMB
HARTFORD FINANCIAL SVCS GRP INC	HIG	KIMCO REALTY CORP	KIM
HASBRO INC	HAS	KINDER MORGAN INC	KMI
HELMERICH & PAYNE INC	HP	KOHLS CORP	KSS
HERSHEY CO	HSY	KRAFT FOODS GROUP INC	KRFT
HESS CORP	HES	KRAFT HEINZ CO	KHC
HEWLETT PACKARD CO	HPQ	KROGER COMPANY	KR
HEWLETT PACKARD ENTERPRISE CO	HPE	L 3 COMMUNICATIONS HLDGS INC	LLL
HILLSHIRE BRANDS CO	HSH	L 3 TECHNOLOGIES INC	LLL
HILTON WORLDWIDE HOLDINGS INC	HLT	L BRANDS INC	LB
HOLOGIC INC	HOLX	L K Q CORP	LKQ
HONEYWELL INTERNATIONAL INC	HON	LABORATORY CORP AMERICA HLDGS	LH
HOSPIRA INC	HSP	LAM RESH CORP	LRCX
HOST HOTELS & RESORTS INC	HST	LAMB WESTON HOLDINGS INC	LW
HUDSON CITY BANCORP INC	HCBK	LAUDER ESTEE COS INC	EL
HUNTINGTON BANCSHARES INC	HBAN	LEGG MASON INC	LM
I D E X X LABORATORIES INC	IDXX	LEGGETT & PLATT INC	LEG
I H S MARKIT LTD	INFO	LEIDOS HOLDINGS INC	LDOS
ILLINOIS TOOL WORKS INC	ITW	LENNAR CORP	LEN
INCYTE CORP	INCY	LEVEL 3 COMMUNICATIONS INC	LVLT
INGERSOLL RAND PLC	IR	LEXMARK INTERNATIONAL INC NEW	LXK
INGEVITY CORP	NGVT	LILLY ELI & CO	LLY
INTERCONTINENTALEXCHANGE GRP INC	ICE	LIN MEDIA LLC	LIN
INTERCONTINENTALEXCHANGE INC	ICE	LINCOLN NATIONAL CORP	LNC
INTERNATIONAL BUSINESS MACHS COR	IBM	LINEAR TECHNOLOGY CORP	LLTC
INTERNATIONAL FLAVORS & FRAG INC	IFF	LOCKHEED MARTIN CORP	LMT
INTERNATIONAL PAPER CO	IP	LOEWS CORP	L
INTERPUBLIC GROUP COS INC	IPG	LOWES COMPANIES INC	LOW
INTUITIVE SURGICAL INC	ISRG	LYONDELLBASELL INDUSTRIES N V	LYB
INVESCO LTD	IVZ	M & T BANK CORP	MTB
IQVIA HOLDINGS INC	IQV	M G M RESORTS INTERNATIONAL	MGM

Company Name	Ticker Symbol	Company Name	Ticker Symbol
MACERICH CO	MAC	NEWFIELD EXPLORATION CO	NFX
MACYS INC	M	NEWMONT MINING CORP	NEM
MALLINCKRODT PLC	MNK	NEWS CORP	NE
MARATHON OIL CORP	MRO	NEWS CORP NEW	NWSA
MARATHON PETROLEUM CORP	MPC	NEXTERA ENERGY INC	NEE
MARRIOTT INTERNATIONAL INC NEW	MAR	NIELSEN HOLDINGS N V	NLSN
MARSH & MCLENNAN COS INC	MMC	NIELSEN HOLDINGS PLC	NLSN
MARTIN MARIETTA MATERIALS INC	MLM	NIELSEN N V	NLSN
MASCO CORP	MAS	NIKE INC	NKE
MASTERCARD INC	MA	NISOURCE INC	NI
MATTEL INC	MAT	NOBLE CORP BAAR	NE
MCKESSON H B O C INC	MCK	NOBLE CORP PLC	NE
MEAD JOHNSON NUTRITION CO	MJN	NOBLE ENERGY INC	NBL
MEADWESTVACO CORP	MWV	NORDSTROM INC	JWN
MEDTRONIC PLC	MDT	NORFOLK SOUTHERN CORP	NSC
MERCK & CO INC NEW	MRK	NORTHERN TRUST CORP	NTRS
METLIFE INC	MET	NORTHROP GRUMMAN CORP	NOC
METROPCS COMMUNICATIONS INC	PCS	NORWEGIAN CRUISE LINE HLDGS LTD	NCLH
METTLER TOLEDO INTERNATIONAL INC	MTD	NUCOR CORP	NUE
MICROCHIP TECHNOLOGY INC	MCHP	NVIDIA CORP	NVDA
MICRON TECHNOLOGY INC	MU	O REILLY AUTOMOTIVE INC NEW	ORLY
MID AMERICA APT COMMUNITIES INC	MAA	OCCIDENTAL PETROLEUM CORP	OXY
MOHAWK INDUSTRIES INC	MHK	OMNICOM GROUP INC	OMC
MOLEX INC	MOLX	ONEOK INC NEW	OKE
MOLSON COORS BREWING CO	TAP	OWENS ILL INC	OI
MONDELEZ INTERNATIONAL INC	MDLZ	P G & E CORP	PCG
MONSANTO CO NEW	MON	P N C FINANCIAL SERVICES GRP INC	PNC
MONSTER BEVERAGE CORP	MNST	P P G INDUSTRIES INC	PPG
MONSTER BEVERAGE CORP NEW	MNST	P P L CORP	PPL
MOODYS CORP	MCO	P V H CORP	PVH
MORGAN STANLEY DEAN WITTER & CO	MS	PACCAR INC	PCAR
MOSAIC COMPANY NEW	MOS	PACKAGING CORP AMERICA	PKG
MURPHY OIL CORP	MUR	PARKER HANNIFIN CORP	PH
MYLAN INC	MYL	PATTERSON COMPANIES INC	PDCO
MYLAN N V	MYL	PAYCHEX INC	PAYX
N R G ENERGY INC	NRG	PEABODY ENERGY CORP	BTU
N Y S E EURONEXT	NYX	PEABODY ENERGY CORP NEW	BTU
NABORS INDUSTRIES LTD	NBR	PENTAIR INC	PNR
NASDAQ O M X GROUP INC	NDAQ	PENTAIR LTD	PNR
NATIONAL OILWELL VARCO INC	NOV	PENTAIR PLC	PNR
NAVIENT CORP	NAVI	PEOPLES UNITED FINANCIAL INC	PBCT
NETAPP INC	NTAP	PEPCO HOLDINGS INC	POM
NEWELL BRANDS INC	NWL	PERKINELMER INC	PKI
NEWELL RUBBERMAID INC	NWL	PERRIGO CO	PRGO

Company Name	Ticker Symbol	Company Name	Ticker Symbol
PERRIGO CO PLC	PRGO	S B A COMMUNICATIONS CORP	SBAC
PETSMART INC	PETM	S B A COMMUNICATIONS CORP NEW	SBAC
PFIZER INC	PFE	S L GREEN REALTY CORP	SLG
PHILIP MORRIS INTERNATIONAL INC	PM	SAFEWAY INC	SWY
PHILLIPS 66	PSX	SANDISK CORP	SNDK
PINNACLE WEST CAPITAL CORP	PNW	SCANA CORP NEW	SCG
PIONEER NATURAL RESOURCES CO	PXD	SCHEIN HENRY INC	HSIC
PITNEY BOWES INC	PBI	SCHLUMBERGER LTD	SLB
PLUM CREEK TIMBER CO INC	PCL	SCRIPPS NETWORKS INTERACTIVE INC	SNI
PRECISION CASTPARTS CORP	PCP	SEAGATE TECHNOLOGY PLC	STX
PRINCIPAL FINANCIAL GROUP INC	PFG	SEALED AIR CORP NEW	SEE
PROCTER & GAMBLE CO	PG	SEMPRA ENERGY	SRE
PROGRESSIVE CORP OH	PGR	SHERWIN WILLIAMS CO	SHW
PROLOGIS INC	PLD	SIGMA ALDRICH CORP	SIAL
PRUDENTIAL FINANCIAL INC	PRU	SIGNET JEWELERS LTD	SIG
PUBLIC SERVICE ENTERPRISE GP INC	PEG	SIMON PROPERTY GROUP INC NEW	SPG
PUBLIC STORAGE	PSA	SKYWORKS SOLUTIONS INC	SWKS
PULTE GROUP INC	PHM	SMITH A O CORP	AOS
Q E P RESOURCES INC	QEP	SMUCKER J M CO	SJM
QORVO INC	QRVO	SNAP ON INC	SNA
QUALITY CARE PROPERTIES INC	QCP	SOUTHWESTERN ENERGY CO	SWN
QUANTA SERVICES INC	PWR	SPRINT NEXTEL CORP	S
QUEST DIAGNOSTICS INC	DGX	ST JUDE MEDICAL INC	STJ
RALPH LAUREN CORP	RL	STANLEY BLACK & DECKER INC	SWK
RANGE RESOURCES CORP	RRC	STAPLES INC	SPLS
RAYMOND JAMES FINANCIAL INC	RJF	STARBUCKS CORP	SBUX
RAYTHEON CO	RTN	STATE STREET CORP	STT
REALTY INCOME CORP	O	STERICYCLE INC	SRCL
REGENCY CENTERS CORP	REG	STRYKER CORP	SYK
REGENERON PHARMACEUTICALS INC	REGN	SUNTRUST BANKS INC	STI
REGIONS FINANCIAL CORP NEW	RF	SUPERVALU INC	SVU
REPUBLIC SERVICES INC	RSG	SYMANTEC CORP	SYMC
REYNOLDS AMERICAN INC	RAI	SYNOPSYS INC	SNPS
ROBERT HALF INTERNATIONAL INC	RHI	SYSCO CORP	SYY
ROCKWELL AUTOMATION INC	ROK	T E C O ENERGY INC	TE
ROCKWELL COLLINS INC	COL	T E CONNECTIVITY LTD	TEL
ROPER INDUSTRIES INC NEW	ROP	T J X COMPANIES INC NEW	TJX
ROPER TECHNOLOGIES INC	ROP	T ROWE PRICE GROUP INC	TROW
ROSS STORES INC	ROST	TAPESTRY INC	TPR
ROWAN COMPANIES INC	RDC	TARGET CORP	TGT
ROWAN COMPANIES PLC	RDC	TECHNIPFMC PLC	FTI
ROYAL CARIBBEAN CRUISES LTD	RCL	TEGNA INC	TGNA
RYDER SYSTEMS INC	R	TENET HEALTHCARE CORP	THC
S & P GLOBAL INC	SPGI	TERADYNE INC	TER

Company Name	Ticker Symbol	Company Name	Ticker Symbol
TEXAS INSTRUMENTS INC	TXN	W E C ENERGY GROUP INC	WEC
TEXTRON INC	TXT	W P X ENERGY INC	WPX
THERMO FISHER SCIENTIFIC INC	TMO	WAL MART STORES INC	WMT
TIFFANY & CO NEW	TIF	WALGREENS BOOTS ALLIANCE INC	WBA
TIME WARNER CABLE INC	TWC	WATERS CORP	WAT
TIME WARNER INC NEW	TWX	WELLS FARGO & CO NEW	WFC
TORCHMARK CORP	TMK	WESTERN DIGITAL CORP	WDC
TOTAL SYSTEM SERVICES INC	TSS	WESTROCK CO	WRK
TRACTOR SUPPLY CO NEW	TSCO	WEYERHAEUSER CO	WY
TRANSDIGM GROUP INC	TDG	WHIRLPOOL CORP	WHR
TRANSOCEAN LTD	RIG	WHOLE FOODS MARKET INC	WFM
TRAVELERS COMPANIES INC	TRV	WILLIAMS COS	WMB
TYCO INTERNATIONAL LTD SWTZLND	TYC	WISCONSIN ENERGY CORP	WEC
TYCO INTERNATIONAL PLC IRELAND	TYC	WYNN RESORTS LTD	WYNN
TYSON FOODS INC	TSN	X C E L ENERGY INC	XEL
U D R INC	UDR	X L GROUP LTD	XL
U S BANCORP DEL	USB	X L GROUP PLC	XL
ULTA BEAUTY INC	ULTA	XEROX CORP	XRX
ULTA SALON COSMETICS & FRAG INC	ULTA	XILINX INC	XLNX
UNDER ARMOUR INC	UAA	YUM BRANDS INC	YUM
UNION PACIFIC CORP	UNP	YUM CHINA HOLDINGS INC	YUMC
UNITED CONTINENTAL HOLDINGS INC	UAL	ZIMMER BIOMET HOLDINGS INC	ZBH
UNITED PARCEL SERVICE INC	UPS	ZIONS BANCORPORATION	ZION
UNITED RENTALS INC	URI	ZOETIS INC	ZTS
UNITED STATES STEEL CORP NEW	X	ZOETIS INC	ZTS
UNITED TECHNOLOGIES CORP	UTX		
UNITEDHEALTH GROUP INC	UNH		
UNIVERSAL HEALTH SERVICES INC	UHS		
URBAN OUTFITTERS INC	URBN		
V F CORP	VFC		
VALERO ENERGY CORP NEW	VLO		
VAREX IMAGING CORP	VREX		
VARIAN MEDICAL SYSTEMS INC	VAR		
VENTAS INC	VTR		
VERISIGN INC	VRSN		
VERISK ANALYTICS INC	VRSK		
VERIZON COMMUNICATIONS INC	VZ		
VERSUM MATERIALS INC	VSM		
VERTEX PHARMACEUTICALS INC	VRTX		
VIACOM INC NEW	VIAB		
VIAVI SOLUTIONS INC	VIAV		
VISA INC	V		
VORNADO REALTY TRUST	VNO		
VULCAN MATERIALS CO	VMC		

Table 20: Data sample of tweeting companies

Company Name	Ticker Symbol	Twitter account	Twitter account
ACTIVISION BLIZZARD INC	ATVI	@erichirshberg	
ADVANCED MICRO DEVICES INC	AMD	@LisaSu	
AETNA INC NEW	AET	@mtbert	
AKAMAI TECHNOLOGIES INC	AKAM	@TomLeightonAKAM	
AMAZON COM INC	AMZN	@JeffBezos	
AMERICAN EXPRESS CO	AXP	@kenchenault	
APPLE INC	AAPL	@tim_cook	
AUTODESK INC	ADSK	@andrew_anagnost	@carlbass
AUTONATION INC DEL	AN	@CEOMikeJackson	
BAKER HUGHES INC NEW	BHGE	@simonelli_l	
BLOCK H & R INC	HRB	@jjones	
C A INC	CA	@MikeGregoireCA	
C M S ENERGY CORP	CMS	@poppepk	
CARNIVAL CORP	CCL	@MickyArison	
CARS COM INC	CARS	@tavetter	
CISCO SYSTEMS INC	CSCO	@ChuckRobbins	
CITRIX SYSTEMS INC	CTXS	@DavidJHenshall	@KirillTatarinov
DISNEY WALT CO	DIS	@RobertIger	
DUN & BRADSTREET CORP DEL NEW	DNB	@BobCarrigan	
EBAY INC	EBAY	@devinwenig	@Donahoe_John
ECOLAB INC	ECL	@CEOEcolab	
EXPEDIA INC DE	EXPE	@dkhos	
FISERV INC	FISV	@jeffyabuki	
GENERAL ELECTRIC CO	GE	@JeffImmelt	
GENERAL MOTORS CO	GM	@mtbarra	
GOLDMAN SACHS GROUP INC	GS	@lloydblankfein	
HOME DEPOT INC	HD	@FrankBlake	
HORMEL FOODS CORP	HRL	@JeffreyEttinger	
HUMANA INC	HUM	@BruceDBroussard	
HUNT J B TRANSPORT SERVICES INC	JBHT	@jbhuntceo	
ILLUMINA INC	ILMN	@fdesouza	
INTEL CORP	INTC	@bkrunner	
INTUIT INC	INTU	@IntuitBrad	
JOHNSON CONTROLS INC	JCI	@amolinaroli	
JOHNSON CONTROLS INTL PLC	JCI	@amolinaroli	
JPMORGAN CHASE & CO	JPM	@emo_jamie_dimon	
JUNIPER NETWORKS INC	JNPR	@ramirahim	@ShayganK
LORILLARD INC	LO	@MurrayKessler	
MCCORMICK & CO INC	MKC	@LKurzius	
MCDONALDS CORP	MCD	@SteveEasterbrk	
MEDTRONIC INC	MDT	@MedtronicCEO	
MICROSOFT CORP	MSFT	@satyanadella	
MOTOROLA SOLUTIONS INC	MSI	@gregbrownmoto	
NASDAQ INC	NDAQ	@adenatfriedman	
NETFLIX INC	NFLX	@reedhastings	

Company Name	Ticker Symbol	Twitter account	Twitter account
ORACLE CORP	ORCL	@MarkVHurd	
PAYPAL HOLDINGS INC	PYPL	@Dan_Schulman	
PENNEY J C CO INC	JCP	@MarvinREllison	
PEPSICO INC	PEP	@IndraNooyi	
QUALCOMM INC	QCOM	@stevemollenkopf	
RED HAT INC	RHT	@JWhitehurst	
RESMED INC	RMD	@ResMedMick	
SALESFORCE COM INC	CRM	@KeithBlock	
SCHWAB CHARLES CORP NEW	SCHW	@WaltBettinger	
SOUTHERN CO	SO	@ThomasAFanning	
SOUTHWEST AIRLINES CO	LUV	@gary_kelly	
STARWOOD HOTELS & REST WLDWD INC	HOT	@tbmangas	@CEOAdam
SYNCHRONY FINANCIAL	SYF	@SYFMKeane	
TERADATA CORP DE	TDC	@VicLLund	
TRIPADVISOR INC	TRIP	@kaufer	
UNUM GROUP	UNM	@UnumRick	
WASTE MANAGEMENT INC DEL	WM	@jimfishwm	
WESTERN UNION CO	WU	@WesternUnionCEO	
WILLIS TOWERS WATSON PUB LTD CO	WLTW	@JohnJamesHaley	
XYLEM INC	XYL	@PatrickKDecker	