What the Tweet is going on?

A Study on how Rumor, Social Media Attention and Twitter Sentiment affects Share Volume

Gustav Hellman[1] **and Jakob Sundqvist**[2]

Gothenburg School of Business, Economics and Law

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[1] gushellmgu@student.gu.se
[2] gusjakosu@student.gu.se

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Abstract

We study rumors and Twitter attention focusing on acquisition transactions and how it affects market reaction, defined as abnormal trading volume, prior to announcement. We study 98 acquisition transactions, were 45 firms had tweets prior the acquisition announcement. We collected tweets one day prior to the announcement and 10 days back and perform sentiment analysis to proxy for investor sentiment. We find with statistical significance that firms with tweets has a 17.1% higher abnormal trading volume than those without, thus enable us to reject the null hypothesis. These findings are in line with previous research on how Twitter sentiment affects the stock turnover. As for how the sentiment in a tweet influences the abnormal trading volume, we can see that tweets with a neutral sentiment do affect the abnormal trading volume by 91,1% at 1% significance. We suggest by our findings that investors are not rational or rightly informed but overreact and trade on the unjustified information betting it could come true.

Contents

Elucidation

Acquisition	A purchase of a business enterprise by another
Acquirer	The purchaser/bidder in an acquisition
Rumor	A story or statement without confirmation by fact
Share Volume	The number of shares/stocks traded on a stock exchange
AVOL	Abnormal Trading Volume; higher or lower trading volume than average
Sentiment	An attitude toward something
Polarity	The positive or negative state of a sentiment
Subjectivity	The subjective state of a sentiment

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1 Introduction

1.1 Background

One could hardly argue other than that today's society is as connected as it has ever been. With social media and transparency, information flows in abundance and is easily accessible. By focusing on listed firms, we expect to retrieve a variety of information concerning the companies, as well as the firm's themselves publish information to investor to be as transparent as possible. However, what about information that are not published by the firm, when the nature of the information, or rather content, with emphasis on the latter- would be considered as a rumor? What effect does that information has on the listed corporation?

When querying that, another question comes to mind, namely which activities that reaches social media, and is it news, or rumors? Along with various expenditures, investments or the overall profitability of a firm, one transaction that creates attention and sentiment is a company acquires another firm. This type of transaction often turns into big news, why one could argue that this type of transaction in the pool of transactions creates attention. Furthermore, rumors and anticipations prior to the actual announcement date is especially interesting as prior to the announcement date, the information is non-public and thus, rumor.

When talking about acquisitions and its recognition as a strategy for, often inorganic, growth, the frequency of deals made are far from sporadic. In a more connected world with developed infrastructure and an accessibility to other markets, the possibility of acquisitions today is endless. Hence, there is no coincidence seeing so many of them. Another argument is, as the world is as connected as has become, it entails a crucial element of business, competition, in which we can see business acquiring firms as a strategy to stay alive in a consolidated market as organic growth isn't enough anymore. When emphasizing the meaning of "strategy" in reaching growth and create shareholder value by acquisitions, such an action clearly creates attention and sentiment not only from investors but also in general. The reason why companies seek to merger with or acquire another company is generally motivated by seeking return, cutting cost or gaining productivity. Moreover, the company could have the agenda to seek new technologies, or the goal to diversify itself by gaining market shares.

Zhang (2017) on “Does Social Media Attention Matter?” caught our interest, by finding that social media attention makes investors more likely to trade. Johan Bollen, Huina Mao and Xiao-Jun Zeng (2011) shows that daily variations in public mood states correlates to daily changes in Dow Jones Industrial Average closing values, making it clear that social media and its tone influences the individual investor sentiment. Zhang (2017) also emphasizes the impact of Twitter by arguing that more people are used to the idea of getting the most up-to-date news from Twitter rather than other news outlets. Therefore, it is reasonable to believe that if acquisitions news gets out early, rumors that is, will appear on Twitter.

The question to ask ourselves is how powerful such platform is in influencing the investors and in turn the stock market. Is there a relationship between rumors, social media attention, investor sentiment and the resulting trading activity? Essentially, do individual investors trade more on firms involved in an acquisition with tweets mentioning them? To answer this question, we collect Twitter data to measure social media attention and investigate whether Twitter attention and trading volume have a relationship.

1.2 Problem Discussion

M&A research are in abundance, but still a rather new subject for research. Analyzing sentiments among tweets is a rather unexplored subject as well, by the fact that Twitter was established 2006. Surely there have been other platforms functioned as a forum for rumors, but not in the same extent as Twitter.

This thesis will contribute and fill the gap of information about how investor sentiment and social media attention affects abnormal trading volume. By focusing primarily on the relation between twitter activity and trading activity, this thesis differ in that prior research primarily focuses on announcement return. Furthermore, by examining the Twitter activity one day prior to the actual announcement date, we can achieve one important goal; we make sure that our approach in investigating rumors captures that and not any data that is subject to the fact that the announcement has taken place. Essentially, the impact of rumor characterizes our entire thesis.

Kenneth R. Ahern and Denis Sosyura (2015) find that media coverage influences financial markets, but there is relatively little evidence on its accuracy. The same report will be the basis of this thesis, in the methodology used by Kenneth R. Ahern and Denis Sosyura, although they used it in a setting of general media and only mergers, we will apply this methodology by focusing on *social* media, by retrieving twitter data, and the center of attention will be firms in acquisition activities.

In the words of Reed (2016), there is little literature relating to stock market trends and the utilization of Twitter data. They also find that social network can proxy for consumer sentiment and that such sentiment significantly affects stock prices. They find that talk intensity of economic issues does not only causes shifts in the daily stock market prices but has a significant negative effect. A response to this would be to contribute to the aggregated research and understanding in connecting Twitter activity and capital markets.

The previous work from Zhang (2017) who examines the impact of social media attention on financial mergers and acquisitions in terms of announcement returns as well as trading activities is an inspiration for us during our research. They mention that another interesting approach in comparing their results is abnormal trading volume, which is another measure that is commonly used to proxy for trading intensity and liquidity, an idea that we will apply. This enables us to achieve a second goal, by examine a similar issue; we can compare our finding with the existing findings and by that further strengthen the finding. Moreover, by using the basis of Zhang's methodology and focus on a different measurement of market reaction, namely AVOL, we can ask the question: do both calculations show to have a similar effect?

In addition, abnormal trading volume can reflect both high and low (good or bad) investor sentiment. While prior research focuses primarily on value creation, trading activity and/or abnormal return, it is also interesting to further investigate *why* such variables are higher than average. Hence, investor sentiment is a good measurement to further investigate the relationship between social media attention and trading activity, not only investigate the attention's impact on trading volume, but also the tone in such attention. Moreover, a lot of research have investigated rumors on twitter in the approach of arguing for misinformation and developing various methods and/or systems for detecting rumors. They have done this by focusing explicitly on rumors, as well as developing methods for sentiment analysis.

Currently, there is a gap in the existing research and literature about how neutral sentiment impact cumulated abnormal return, stock turnover or abnormal trading volume. Researchers often exclude it (Koppel and Schler, 2006) but we want to explore the effect of further analyze neutral sentiments. The neutral aspect of a tweet is interesting especially when the neutral sentiment can be broken down to how much of an opinion or to what extent a tweet is explaining something, looking at the degree of polarity and subjectivity. We aim to fill in this gap. The result of this thesis could also form the basis of a management´s social media strategy.

1.3 Aim

This thesis aims to investigate if social media attention, measured by the number of tweets, focusing on acquisition transactions, and how it affects market reaction defined as abnormal trading volume, prior to the announcement.

1.4 Research Question

How does rumor, social media attention and Twitter sentiment impact share volume?

The main research question above gives rise to the following sub-questions that will guide this thesis:

- Does rumor prior to an Acquisition affect share volume?
- How does Twitter sentiment impact share volume?

1.5 Delimitations

M&A activity has been widely investigated with various angles, why only the most relevant and applicable prior research will be considered.

In the scope of this thesis, we will not differ on institutional and retail (individual) investors, but rather the marginal investor. In addition, we will not account for share volume after the M&A transaction as the information no longer is considered as rumor.

Furthermore, throughout this text: mergers & acquisitions, M&A and deals are the same meaning, although the meaning may differ in some occasions, it does not affect our context. Furthermore, in alignment with Papadopoulos (2018), we will refer abnormal trading volume as AVOL.

Moreover, we will only account for acquisitions and not mergers. In acquisitions, we will apply an acquirer perspective, meaning that we analyze the impact of social media attention on acquirer share volume.

2. Theoretical Framework

In this section, we present our theoretical framework from which we in the next section will define our hypotheses.

The area of Mergers and Acquisition is a widely researched topic in the field of finance theory, and mainly focuses on how mergers and acquisition create value from different aspects, as well as announcement return.

2.1 (No) Perfect Market

According to the previous findings from Thomas L. Hazen, there must be a thin balance between the investors' access to the relevant market information and the management's desire for secrecy (1987). Hazen further discusses that the management of firms have a legitimate motive in not disclosing a potential deal during the deals early stage, because of the risk to interfere with the process of the negotiations. Hazen also explains why Merger and Acquisition deals and its market is so significantly affect by rumors. The nature of corporate takeovers, restructuring, private equity deals combined with investors' ignorance as to mergers and acquisitions in their early stages of planning, results in a volatile market affected by rumors. He also argues that under the circumstances of an efficient capital market hypothesis, the markets price reflects all the information available for the market. Furthermore, Fama (1991) define a perfect capital market where price fully reflects the signals of resource allocation. An efficient market is when firms and investors can make decision regarding investments or choose between different securities that fully reflects the all-available information on the market. Moreover, Hazen also discusses the presence of misinformation and false rumors that circles around and that the efficiency of the market is hampered by the environment of investors' scrutiny for stocks that may be involving a possible deal. Finally, he finds that the main problem is not the absence of information to merger negotiations, but rather the existence of half-truths that corporate spokespersons disseminate.

Again, attention and trading have a relationship on a market characterized by the fact that it is not perfect. The assumptions of asymmetric information theory imply that one party has more knowledge than the other does, M&A's particularly, are subject to asymmetric information. Taking this further, implying that Twitter is a possible *forum* for asymmetric information, readers and users are affected.

2.2 Media Attention

Bushee et al. (2010) find that business press serves as an information intermediary, which we believe twitter have become today for investors. As the paper shows, with bigger press coverage, it significantly reduces the degree of information asymmetry during earnings announcement periods and that a broad dissemination of information has a higher impact than the quantity or the quality of the information given out by the business press. Furthermore, Dougherty et al. (2013) argues that along with twitters increase in popularity, the social media platform also simultaneous has become a forum for broadcasting rumors, and false news. Zhang (2017) further states that more people are used to the idea of getting the most up-to-date news from Twitter rather than other news outlets, showing the impact of Twitter.

2.3 Investor Sentiment

Markum Reed (2016) in how Social Network effects the stock market, find consumer confidence as an economic indicator that measures the consumers' feelings concerning the overall economy's situation and applying this to twitter, which makes their paper highly relevant to our thesis. Reed (2016) applies a lexicographic, a way of sorting words in alphabetic order, and a widely used method in computer science. The lexicographic analyze twitter data over a period of three months and find that talk intensity of economic issues not only causes shifts in the daily stock market price, but also has a significant negative effect Reed (2016). These findings tell us that twitter has become a part of the investors' news spectrum, which influences the investors trading. These results are vital for us, as instead of focusing on the *return*, we want to see if Twitter affect *volume*. In other words, another measurement of market reaction.

Another interesting aspect of the research of the relationship between Twitter activity and the capital market is Mittal & Goel (2011) in which they question the correlation between the people's mood and their investment decisions, in that there is no direct correlation proven between the people who invest in stocks and who use twitter more frequently. Although it certainly exists an indirect correlation, the moods of people around them may be the effect of investment decisions.

By focusing on not only rumors but also how rumors tend to be classified as positive or negative, Steven F. Cahan, Chen Chen & Nhut H. Nguyen (2013) find that when firm-specific media sentiment is positive, investors overreact to positive earnings surprises. Likewise, when the sentiment is negative, investors overreact to negative earnings surprises. Further, their results suggest that the tone of news items can contribute to the misevaluation of stocks, and that this effect is incremental to market-wide investor sentiment. Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand (Malcolm Baker & Jeffrey Wurgler, 2007).

Sentiment analysis aims to analyze Twitter data to measure the public mood in a variety of methods and is common in analyzing public mood. Anshul Mittal and Arpit Goel (2011) analyze the sentiments and capture the public mood from Twitter feeds. In the same topic, Sprenger and Welpe (2011) find that the absolute value of cumulative returns prior to a news event are more pronounce for positive news than they are for negative news, suggesting more widespread information leakage before good news. When translated into our approach, twitter sentiment is shown to have an impact on stocks. Although, the correlation of their and our approach, return and volume, is not clear. We cannot expect to see similar results, meaning when attention affect cumulative return, abnormal trading volume shows the same direction of effect. In that, Ying (2007) show that momentum profit is higher and more persistent among stocks with low abnormal trading.

By focusing on news that are not justified by the facts at hand, namely rumors, Goetzmann and Massa (2005) suggest differences in opinion often trigger higher trading volume, resulted from more trades by optimistic traders or from hedging-motivated trades because of increasing uncertainty. Barder and Odean (2008) hypothesize that individual investors are net buyers of attention grabbing stocks, whereas investors consider purchasing only stocks that first caught their attention. They further highlight that stocks that are experiencing high abnormal trading volume is an example of this. In other words, social media attention, such as Twitter, is attention grabbing which in turn could result in high abnormal trading volume, creating something in line with of a compounded interest effect.

When conducting a sentiment analysis, the most usual method of conducting the results is by dividing the message into neutral, positive or negative. Moreover, if the results are neutral, there is more information to analyze. Koppel and Schler (2006) give evidence on the value of further analyze the neutral aspects of a sentiment test. They conclude that it is crucial to examine the degree of neutrality by looking at the polarity of a meaning. They further discuss the rationality by excluding the neutral sentiment to solve the issue for binary positive and a binary negative variable. They argue, however, that it is important for research within sentiment analysis to include the neutral sentiment. However, Bagheri, H., & Islam, M. (2017)

find that social networks are the main resources for gathering information about opinion and sentiments in which they realize, that the neutral sentiment for tweets are significantly high, showing the limitations of the current studies.

2.4 Market Reaction

Zhang's (2017) work is used as a theoretical framework in this thesis and in certain way the backbone. Zhang (2017) measures the stock turnover as the abnormal stock turnover between the event window –10 and +3 of an acquisition transaction and examines the impact of social media on financial mergers and acquisition activities. They collect Twitter data to proxy for social media attention and find a relationship between the positive sentiment of a tweet and the stock turnover involving an acquisition transaction. They investigate in a way in which tweets effect the investors to trade on a specific news flash, connected to the theories of behavioral finance and moreover theories of asymmetric information. In addition, we use their definition of that higher stock turnover indicate more intense trading activity, translated into abnormal trading volume.

Furthermore, Gao and Oler (2011) also focuses on rumors and find that rational investors' trade on the markets´ perceived overreaction to takeover rumors, an indication that media affect investor sentiment and in turn affects stock prices. In the same context, Tetlock (2011) focuses on "bad" rumors and find that the individual investors overreact to news that signifies as stale when this stale news is about publicly traded firms. On the same subject of news, Zhang (2017) says that the idea is individuals are more likely to chase familiar stocks, meaning the stocks they hear about. Therefore, if social media attention is as effective and influential as the traditional news media, we should observe more trading activity, meaning higher stock turnover during the event period.

Recent studies in market reaction on abnormal trading volume are not in abundance. Researchers tend to investigate stock price or the cumulated abnormal return during the pre-announcement period. Jarrell and Poulsen (1989) examines 172 successful takeovers between 1981 and 1989, focusing on price stock prices and trading volume. They show evidence on stock price run-ups and a raise in trading volume before a transaction. Moreover, they also show indication that the existence of rumors in the news is a strong variable for explaining unanticipated premiums and pre-bid runup for tender targets. They also investigate the trading volume and show significance of mean adjusted abnormal trading volume prior an announcement. According to their results, a level of abnormal trading activity over the pre-announcement window is present.

There are different approaches to calculating abnormal trading volume. According to Papadopoulos (2018), is it possible to measure the market reaction as abnormal trading volume by taking the event window average divided by the mean of 100 days scaled by the outstanding shares, AVOL. This enables us to capture the market reaction of twitter activity surrounding acquisition transaction prior to the official announcement.

Further, Timothy R. Burchy (2014) find that twitter is a favorable strategy to get attention from investors, with investors characterized as limited in attention from news. In finding that and applying to our approach, one must clarify that their findings are from the firm's perspective, but one could also argue that the findings are to be generalized in arguing that twitter is a well-known forum for business news and investors seems to be aware of it. Although, the findings above can also explain the impact of rumors and "half-truths" with investors having difficulties, or even unwittingly, trading on information that is not in fact information, but rumor.

In addition, Keown and Pinkerton (1981) find that merger announcements are poorly held secrets and trading on this nonpublic information abounds. They also find that leakage of inside information is a pervasive problem occurring at a significant level up to 12 trading days prior to the first public announcement. Moreover, information leakage has an impact on trading and can according to Chou et al. (2010) be profitable. We should hence expect an abnormal trading volume in our study.

Zivney et al. (1996) show that the market overreacts to takeover rumors, where "market" reasonably translates to trading activity. Furthermore, Yuan Gao and Derek Oler (2011) argue that significant trading activity can reflect the interaction between traders who are betting that a takeover rumor is true and those who are betting the same rumor is false. Furthermore, Harris and Raviv (1993) show that even though traders share common prior beliefs and receive common information, they might still differ in the way they interpret that information. Meaning, in some cases we interpret the information differently, in some cases we simply betting on it being true or false.

2.5 Summarizing Theory

These theories are somewhat built as a response to the widely known theory of perfect capital markets. The united findings when talking about rumors and their market reaction is clearly showing that capital markets are in fact not perfect and efficient.

In previous research and findings, the academy seems to reach consensus in stating that if any rumor exists, we should expect to read it on Twitter. Further, along with Bushee (2010), the actual spread of the tweets would have a greater significance than the actual quality of the tweets. Hazen also points out that M&A deals and its market is significantly affected by rumors, and along with Keown and Pinkerton (1981) findings, where merger announcements are poorly held secrets and leakage of inside information occurring up to 12 trading days prior to the public announcement, showing rumors impact on the market.

3 Hypotheses

We will in this chapter display what we, with a standpoint from the sub- questions as well as theoretical framework expect from the study. The hypotheses will be tested with regression analysis whereby identifying if the variables are shown to have a significant relationship.

3.1 Social Media Attention and Share Volume

Does rumor prior to an Acquisition affect Share Volume?

According to Zivney (1996), we should observe an abnormal trading volume. Although they do not focus on social media specifically, we expect to see similar results with rumors on social media, consistent with theoretical models of noise and liquidity traders. We also expect that the share volume will be significantly higher than the average trading volume. This would be rather intuitive, also for the short-term frame effect, as in the long-term, it would not be a rumor anymore. Our first hypothesis is therefore:

Hypothesis 1: The share volume will be higher with firms having rumor on Twitter than the ones without

Furthermore, Yuan Gao and Derek Oler (2011) find that rational investors' trade on the markets' perceived overreaction to takeover rumors, and Reed (2016) who find that talk intensity of economic issues not only causes shifts in the daily stock market price, but also has a significant negative effect. It signals that rumors have an impact on share volume. In alignment, Zhang (2017) said that individuals are more likely to chase familiar stocks and Jarrell and Poulsen (1989) who showed evidence on a raise in trading volume before the official transaction/announcement, this leads us to our second hypothesis:

Hypothesis 2: More Twitter attention, measured by number of tweets, will result in higher abnormal trading volume.

3.2 Twitter Sentiment and Share Volume

How does Twitter sentiment impact share volume?

Zhang (2017) find that firms are more likely to have positive stock returns when there is a positive tone in tweets about merger news. With our approach in investigating trading volume instead of stock returns, and acquisitions instead of mergers, we expect to see the same tendency in our thesis.

Investors expected to be well updated Twitter and thus influenced by the average sentiment and would hence trade on that sentiment.

Zhang (2017) mentions that Goetzmann and Massa (2005) suggest differences in opinion often trigger higher trading volume. Zhang further find a relationship between the positive sentiment of a tweet and the stock turnover involving an acquisition transaction. In addition, Mittal & Goel (2011) stated that there is no direct correlation proven between the people who invest in stocks and who use twitter more frequently, although an indirect correlation certainly exists.

Barder, Odean (2008) hypothesized that individual investors are net buyers of attention grabbing stocks. Harris and Raviv (1993) further showed that even though traders share common prior beliefs and receive common information, they might still differ in the way they interpret that information. Hence, we expect that Twitter sentiment should affect share volume. Our third hypothesis is:

Hypothesis 3: Aggregated positive or negative sentiment results in Abnormal Trading Volume.

3.3 Subjectivity and Polarity within Neutral Sentiment

From the previous research, it has been proven that Twitter sentiment do affect trading activity. As Koppel and Schler (2006) said, neutral sentiments are not to ignore and the emphasis on that it is a further dimension within neutral sentiment to explore.

Because no prior research has studied the relationship between subjectivity and polarity and trading volume, abnormal trading volume included, we cannot directly hypothesize our results with existing literature. However, when studying neutral sentiments, we expect that they differ within its characterization and by that saying that people's emotions and opinions affect the investors, thus formulating our fourth and final hypothesis:

Hypothesis 4: The higher the subjectivity and polarity, respectively, is within neutral sentiments, the higher the abnormal trading volume.

4 Methodology

We will in this section present our approach to quantitative data selection. We divide our sample construction into different steps and we will here clarify each step and the choices behind them. This is to collect the relevant and applicable data to ensure quality, relevance, validity and reliability, as well as giving the reader a clear view of our approach in investigating our research question.

4.1 Time Frame

To make our result more suitable for comparison with Zhang (2017), we look at the biggest 250 M&A deals that occurred on the North American market. The reason of this is that bigger M&A-transactions have a higher tendency of having tweets surrounding them.

Essentially, we want to capture the effect off Twitter on M&A-transactions and their acquirer trading volume before the public announcement. In addition, since Twitter data is the greater part of this thesis, we cannot go back further than March 21, 2006, the date at which Twitter were founded. This gives us a time span of 12 years.

4.2 Collecting Data

4.2.1 Acquisitions and their Announcement Date

To collect data surrounding rumors concerning acquisitions, we first identify completed and/or announced acquisitions. We retrieve this data from Zephyr by searching M&A´s filtering USA, time span 2006 to 2018 and searching by the top 250 acquisitions deals, seen as deal value. To enable us to retrieve stock data, the acquirer firm must be publicly listed. After witch, we investigate whether the acquisition had Twitter activity prior to the actual announcement of the transaction. Our final data selection consisted with 48 transactions with tweets, and 98 without tweets. To enable us to compare the transactions with and without tweets, we paired the two samples, leaving us with 96 transactions.

4.2.2 Twitter Data

Twitter is a social media that lets the user write a short text up to 140 characters, enabling the user to share their ideas. To this date, twitter have around 330 million monthly users, generating 500 million tweets per day (OmnicoreAgency, 2018). Twitter has been growing and has according to their latest fiscal Q4 report of 2017 330 million monthly users (Twitter, 2018), making Twitter an important platform for traders, investor and companies.

In recent years, there have been a lot of research on how twitter affect share price and cumulated abnormal return. Bhagwat and Burchy (2014) find that the degree of announcement return is increasing and have a relation with the percent of tweets regarded as financial. Many studies have been made on how news and how media attention affects stocks and their return. However, how tweets affect M&A deals looking at abnormal trading volume is nearly undiscovered.

We look at a (–10, -1) window, meaning we look back 10 days prior to and up to the day before the announcement of an acquisition transaction to collect tweets and retweets mentioning the transaction. The reason why we choose the event is that we want to capture the core impact of tweets and the social media attention on the trading activity before the official announcement. It is obvious that the trading activity will increment at the announcement, why we excluded this from our event window. In the interest of apprehending the abnormal trading volume before the announcement, we do not examine the cumulative abnormal return as (Vineet Bhagwat Timothy R. Burchy 2014) and Zhang (2017) did, why we do not focus on the days after the announcement.

With the retrieved acquisitions and their announcement date, we collect Twitter data. We manually collect tweets by the twitter advanced search application, enabling us to specify the time span of interest and our key words to identify tweets mentioning a transaction. The words we search are “acquisition”, “offer”, “deal”, “buy”, “acquire”, “bid” and “rumor”, independently. These words are classified as neutral according to the NLTK sentiment analysis program. With the key words, we searched the acquirer and target firm as "topic" and thus retrieved the firms of interest. We exclude Tweets that are directly from the acquiring firm as well as tweets in other languages. For every tweet, we gave it a count of one. With the tweets and their respective re-tweets, we aggregated the data with a total of tweets of the respective transaction. The variable for number of tweets is skewed why we choose to make the number of tweets as a dummy variable, where every tweet above median undertake one and zero otherwise.

4.2.3 Trading Volume

We retrieve the trading volume data from Wharton Research Data Services, WRDS. This data is the basis for the calculation of abnormal trading volume, which we under ´calculating AVOL´ will clarify.

4.2.4 Collecting and Managing Control Variables.

As stated earlier, Zhang's motivation for control variables were to account for a company's key performance measurement (2017). In investigating our research question partly with the aim to compare with Zhang's findings, it is reasonable to look at the same control variables. In collecting control variables, we did however drop Market Value to Book Value due to high correlation to Operating Cash Flow to Market Value.

To start with, we use Tobin's Q, measured as the market value of a company scaled by the replacement value of the firm's assets, meaning that Tobin's Q measures if the stock is undervalued or undervalued. It captures the investors aggregated believes about a firm and could hence have a bigger impact on trading volume when rumor gets out. Other key measurements of performance we used were Operating Cash Flow to Market Value, Cash to Total Assets and Market Value to Book Value, all retrieved from Orbis. Market value is defined as shares outstanding times share price at time t. We used the relevant financial data at the end-of-the-year financial statement the year at which the transaction occurred.

The intuitive interpretation of using Deal Value is that it could affect the overall attention among the public. We retrieve this variable in thousand euros from Zephyr from the respective acquisition transaction. The variable was skewed in its distribution and to control for significant differences in deal value sizes, we convert it to logarithmic form.

4.3 Managing Data

4.3.1 Sentiment Analysis

In sentiment analysis, the bigger picture is what is expressed and if there is a sentiment behind it. In other words, are the Tweets “neutral”, “negative”, or “positive”?

To analyze the Twitter data, we use the application NLTK 2.0.4, a leading platform in interpreting human language data for the coding program Python. The application classifies whether the tweet expresses a positive, negative or a neutral sentiment. For instance, "This deal is a good deal" would be a positive sentiment according the application, extracting the word ´good´ as positive, for instance. "This deal is going to be a bad deal" is a negative sentiment, and "we are hearing rumors about a deal coming up" is a neutral sentiment, with a polarity of 0.2 and a subjectivity of 0.8. The application is using a hierarchical classification system where neutrality is determined first, then sentiment polarity along with sentiment subjectivity, if the tweet is neutral. Polarity and subjectivity are measured from a scale of 0 to

1, where Polarity measures how strong positive or negative a tweet is when it has been classified with a sentiment, and the subjectivity amplifies how much of an opinion it is.

The application has some limitations when tweets are sarcastic or if they include links to website or photos. We solved the former by eliminating the tweet if we identified the sarcasm. However, sarcasm is subjective and, in some cases, hard to detect, thus we may have missed some sarcastic tweets, making a possible negative or positive analyzed as neutral. That would however not affect our analysis, as the scope of this thesis is to capture the overall effect, and the fact that we excluded approximately six or seven tweets due to sarcasm. The latter were solved by eliminate the website and/or picture. The third disadvantage of the application is the accuracy of the sentiment analysis. However, the expected margin of error is so small that the impact is negligible. Although, when analyzing the tweets with the application and not manually, we ensure that the sentiment analysis is consistent.

4.3.2 Calculating AVOL

We will in this section present our calculation of Abnormal Trading Volume, AVOL. Worth mentioning is that Zhang (2017) argued that stock turnover instead of trading volume can alleviate the concern of size effect as it is scaled by the number of shares. In our calculation of AVOL, however, by the calculation of Papadopoulos (2018), we are able to scale the share volume by number of shares, thus control the size effect.

Trading volume is defined as the number of shares of firm i traded on day t, scaled by the total number of shares outstanding of firm i traded on day t (Papadopoulos, 2018). The normal trading volume, in alignment with this, is a 100 days' average from the day prior to the announcement.

Looking at the day prior to the announcement for the respective transaction and 10 days back, trading volume were retrieved for the trading days and then computed as the average over the (-10, -1) event window.

After calculating the average trading volume over 100 days prior to the day before the announcement as well as the event window average trading volume, we finalize the calculation of abnormal trading volume in alignment with Papadopoulos (2018). According to which, abnormal trading volume is measured as the average trading volume over an event window scaled by the average trading volume over a 100-days estimation window.

4.3.3 Controlling for Contemporaneous Events

What trading activity is to do with rumor and what is not?

Our time nor data are enough to exactly control that AVOL really occur because of twitter attention and rumor. A possible phenomenon to control for is media attention that is not social media. Our analysis shows a relationship in which most other factors are not significant. We believe that by benchmark those firms who had tweets with those who had not, the factor of coincidence is small. We can thus conclude that by proxy for social media attention, we can lay the ground for what *should* be the basis for higher trading volume.

4.3.4 Robustness Test

Unlike Papadopoulos (2018) model for calculating abnormal trading volume, we sought out for an alternative calculation of abnormal trading volume. In the same formation, instead of the 100 days' average, we calculated a 365 days' average. In the goal of capture the total effect in a full year, we later realized that we in taken too many trading days into our calculation probably captured other big events and by that miscalculating the normal share volume. The calculation used in this thesis is thus based on the 100 days' average.

4.4 Analyzing Data

4.4.1 Cross-Sectional Regression Analysis

We finalize the gathered information in a regression analysis, with Abnormal Trading Volume with social media attention and sentiments along with control variables. In investigating AVOL with head variable of interest along with control variables, we want to capture the overall impact. With regression analysis, it enables us to examine several variables simultaneously. Using multiple cross-sectional regression analysis is a well-established method in analyzing this type of issue with several possible independent variables, why the use of this model is suitable for us. The general formula for multiple regression analysis with k independent variables is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

In this thesis, the dependent variable is AVOL, by which we reformulate the function as:

$$AVOL_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

In our model, we made sure not to violate the key assumptions of linear regression for reliable and consistent results, in which we will use the residuals as an estimate of the error term. Seven required assumptions of regression analysis are controlled for (Jaggia & Kelly, 2013, p.476):

1. The regression model is linear in the parameters with an additive error term: Applying a linear model does not violate the assumption of linearity.

2. There is no exact linear relationship among the explanatory variables, there is no perfect collinearity: To prevent perfect collinearity, a correlation analysis show that the independent variables did not highly correlate with each other. Further, reasonably low coefficient of determination along with significant explanatory variables strengthens this assumption.

3. Zero conditional mean: It is possible that a variable not used possibly explains our dependent variable, thus not explaining the dependent variable sufficiently. In collecting variables reasonably capturing the characteristics of the deals and firms, we believe this error is small.

4. The variance of the error term is the same for all observations, the error term is homoscedastic: To ensure that the variance of error terms is similar across observations, to ensure homoscedasticity, we plot the residuals against explanatory variables and observe equally distributed points.

5. The error term is uncorrelated across observations, there is no auto correlation: Plotted residuals show no serial correlation.

6. The error term is not correlated with any of the explanatory variables. There is no endogeneity: Correlation analysis show no endogeneity.

7. The error term is normally distributed: Plotted residuals proves this assumption.

5 Regression Results and Analysis

In this section, we present our empirical result. Summary statistics are presented first. We will then test our hypotheses.

Table one below shows the average, median, minimum value and maximum value of our explanatory variable ´number of tweets´ along with our control variables.

Table 1. Summary Statistics

	Mean	Median	Min	Max
Number of tweets	159,7553	60,5000	3,0000	7 300,0000
Deal value, thd euro	17 526 624	12 506 638	4 629 691	115 400 000
Tobins' Q	1,9106	1,53	0,4700	6,1900
MV/BV	138,3794	9,3992	-4 475,5611	18 341,5032
Operating Cash Flow/Market Value	0,0058	0,0002	0,0000	0,1089
Cash/Total Assets	0,1300	0,0381	0,0001	3,6010

5.1 Social Media Attention

5.1.1 Tweet Dummy and Number of Tweets

To test our first hypothesis, we wanted to find evidence of significant relationship between the abnormal share volume and transactions having tweets prior to announcement, as well as the impact of number of tweets.

To test this relationship, we performed a regression analysis including the explanatory variable, abnormal share volume, with a dummy variable testing if tweets influence AVOL. The variable takes the number one if when the acquirer has tweets, and zero otherwise.

Looking at table 2 and our first regression output, we conclude that at a 5% significance, acquisitions with tweets has an 18, 2% increase on the AVOL compared to those without. Consistent with our results, Gao and Oler (2011) find that investors trade on the markets' perceived overreaction to takeover rumors. Further Zhang (2017) said that individuals are more likely to chase familiar stocks.

Barber, Odean (2008) further states that individual investors are net buyers of attention grabbing stocks, also in line with our findings. Moreover, Zivney et al. (1996) declare signs that the market overreacts to takeover rumors and as abnormal trading volume is significant, we can draw the conclusion that the market reacts the same in our case as well. The same findings correlate to Jarrell and Poulsen (1989) in seeing a raise in trading volume before a transaction. Furthermore, Zhang's (2017) results on stock turnover had a coefficient of 14,23% increase, compared with our result at 18.2%. Our first hypothesis, that the share volume will be higher when firms having rumor on Twitter compared with the ones without, is correct.

By account for the number of tweets, we tested the dummy variable for number of tweets over median to test if acquisitions with 60.5 tweets or more affects AVOL. By including this dummy variable, the regression results in the second output demonstrates that acquisitions with number of tweets over 60.5 has a 17,6% higher AVOL than those acquisition with tweets under 60.5. Zhang (2017) further find number of tweets to have an impact on stock turnover. Thereby concluding that our second hypothesis, that more Twitter attention will result in higher abnormal trading volume, is correct.

Bushee et al (2010) can explain why number of tweets has an impact and why Twitter affect investors. Their results show that the quantity of news or rumor is more effective than the quality of it, in our case the spread of the tweets has a greater significance than the actual quality of the tweets. Also consistent is Timothy R. Burchy (2014) saying that twitter is a favorable strategy to get attention from investors.

We performed robustness check with our method of calculating the AVOL to test the data with another approach that do not have support by previous work. However, we wanted to see if an untested method as our AVOL show similar effect. The regression results in the third output show that at a 5% significance level, abnormal trading volume is 19% higher with acquisitions having tweets than them without. Our calculation did not however work with dummy number of tweets.

AVOL shows the impact of events in a specific time window, compared to the normal trading volume. In our calculation, we defined normal trading volume as one-year average.

However, assuming that normal trading volume is smoothen out in calibrating fluctuations and abnormality, when taking the average trading volume for the –10 days prior an announcement scaled by the one year mean trading volume, the one-year average could account for other big events and thus miscalculate the normal share volume.

Table two found below.

Table 2. Impact of Tweets and Number of Tweets

This table presents the regression results of the following equations: left hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Tweet\ dummy\ i,t$, middle, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Dummy\ number\ of\ tweets\ i,t$, right hand side, our robust calculation, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Tweet\ dummy\ i,t$, where Tweet Dummy takes on 1 if the deal i has tweets at time t and 0 otherwise, dummy number of tweets takes on 1 if deal I has tweets over its median at time t and 0 otherwise. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Variable	Abnormal Trading Volume		
Tweet Dummy	0.182**		0.190**
	(0.071)		(0.082)
Dummyinumberiofitweets		0.176*	
		(0.089)	
Constant	0.985***	1.029***	-0.039
	(0.045)	(0.039)	(0.047)
N obs	93	93	94
R-squared	0.069	0.046	0.056
	F(1, 91) = 5.96	F(1, 91) = 4.43	F(1, 92) = 5.36
Prob > F	0.0165	0.0382	0.0228

5.1.2 Tweet Dummy and Number of Tweets with Control Variables

When further analyzing abnormal trading volume as dependent variable, with Tweet dummy and dummy number of tweets along with control variables, Tweet dummy is still significant at a 5% significance, further strengthened by Jarrell and Poulsen (1989). However, dummy number of tweets is no longer significance, stating that with control variables, we cannot conclude that number of tweets impact trading volume. In addition, we did two separate regressions as the two main variables showed high correlation.

Furthermore, Tobin´s Q is significant at a 5% level within both regression results. To make a fair evaluation from our results from the regression analysis with incorporating control variables, we look at Zhang (2017) results with control variables. Zhang obtained comparatively results, where Tobin's Q were significance at 5% at the event window Zhang tested. Other control variables were not significant.

The regression model with control variables did not fit our own calculation, why we had to exclude it, thereby showing that our calculation have an impact on share volume, but not valid with control variables. This could be because of the skewed and rather small sample, as Zhang (2017) find number of tweets with control variables to be significant.

Table three found below.

Table 3. Impact of Tweets and Number of Tweets with Control Variables.

This table presents the regression results of the following equations: on the left-hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Tweet\ Dummy\ i,t + \beta 2 * Xi,t + \beta 3 * Y\ j,t.$ On the right-hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Dummy\ number\ of\ tweets\ i,t + \beta 2 * Xi,t + \beta 3 * Y\ j,t.$ Where Tweet Dummy takes on one if the deal i has tweets at time t and 0 otherwise, dummy number of tweets takes on 1 if deal I has tweets over its median at time t and 0 otherwise. Xi, t are variables that capture the characteristics of the deal and $Y\ j$, t measures firm j's characteristics at time t. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Variable	Abnormal Trading Volume	
Tweet Dummy	0.171**	
	(0.074)	
Dummy number of tweets		0.171
		(0.104)
Tobin's Q	-0.125**	-0.111**
	(0.049)	(0.053)
Cash to Total Assets	0.712	0.706
	(0.507)	(0.517)
Deal Value, log	-0.020	-0.048
	(0.053)	(0.055)
Operating Cash Flow to Market Value	-47.697	-46.833
	(75.114)	(75.746)
Constant	1.494*	1.961**
	(0.869)	(0.889)
N obs	92	92
R-squared	0.130	0.107
	F(5, 85) = 2.88	F(5, 86) = 2.49
Prob > F	0.0189	0.0372

5.2 Sentiment Analysis

5.2.1 Impact of Negative and Neutral Sentiment on Share Volume

In our third regression analyzing sentiment´s impact on abnormal trading volume, the negative sentiment is significant at a 1% level. The negative coefficient shows that an increase in tweets with negative sentiment, we should see a lower trading volume by 56,6%. Neutral sentiment is also significant at a 1% level showing that an increase in tweets with neutral sentiment, abnormal trading volume increases 62%. However, the positive coefficient can be interpret by the fact that most of the tweets were neutral and the overall effect of tweets affect trading volume.

The variable for positive sentiment did not fit the model why we had to exclude it. A possible explanation is due to a skewed distribution, or the fact that in alignment with Sprengler and Welpe (2011) saying that more widespread information leakage having a bigger impact rather than good news, or showing the possible limitation of the sentiment analysis application in classifying positive sentiment. Thus, we cannot compare our results to Zhang's (2017) finding of the relationship between trading activity and positive sentiment. However, we do expect that variable to have a positive impact on trading volume.

Furthermore, in Mittal & Goel's questioning about the direct correlation between the people's mood and their investment decisions, although it certainly exists an indirect correlation, our results suggest that neutral sentiment has the biggest overall effect, stating that the bigger effect on abnormal trading volume is the overall effect of tweets rather than the sentiments behind them. In alignment with Bagheri, H., & Islam, M. (2017) in realizing that the neutral sentiment for tweets are significantly high, showing the limitation of the current works, our results suggest likewise.

Moreover, Goetzmann and Massa (2005) suggested that differences in opinion often trigger higher trading volume. Having neutral, positive and negative tweets and then aggregate them; the analysis bases on aggregated sentiment. The analysis shows neutral and negative sentiment to be significant, hence in line with Goetzmann and Massa (2005). This leads us concluding our third hypothesis, aggregated positive or negative sentiment results in a higher trading volume than the firm average*,* is correct. However, we cannot draw any conclusions about positive sentiment.

In addition, Harris and Raviv (1993) showed that even though traders share common beliefs and receive common information, they might still differ in the way they interpret that information. Meaning it could be hard to measure the sentiment in having an impact on share volume, as we cannot assume individuals interpret the information consistently, this could also be the reason why our positive sentiment did not work in the model.

Table four found below.

Table 4. Impact of Neutral and Negative sentiment.

This table presents the regression results of the following equations: left hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Negative\ Sentiment\ i,t.$ Right hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Neutral\ Sentiment\ i,t.$ Where Negative Sentiment and Neutral Sentiment, respective, is the characteristics of tweets about deal i at time t. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Variable	Abnormal Trading Volume	
Negative Sentiment	-0.566***	
	(0.197)	
Neutral Sentiment		0.620***
		(0.206)
Constant	1.267***	0.703***
	(0.078)	(0.153)
N obs	45	45
R-squared	0.060	0.125
	F(1, 43) = 7.53	F(1, 43) = 8.51
Prob > F	0.0088	0.0056

5.2.2 Sentiment Analysis with Control Variables

In our fifth table, we present the sentiment analysis among with control variables as well as interaction variables calculated as the respective sentiment variable times number of tweets, showing a more complete impact of sentiments.

The regression analysis on the left-hand side shows the impact of neutral sentiment along with control variables with a significance at the 1% level, stating that with higher number of neutral tweets, abnormal trading volume increases with 91,1%.

In our second regression analysis, analyzing the negative interaction variable with control variables, we can state that at 1% significance, we expect that for each negative tweet, abnormal trading volume to be –0.003 lower.

When doing a regression with sentiment positive, negative along with their respective interaction with number of tweets as well as number of tweets, number of tweets showed a high correlation to the other variables and thus showed a coefficient equal to zero, why we had to exclude it in our presentation. The negative interaction variable, however, showed to be significant at 5% level why we choose to analyze that variable along with control variables.

Table five found below.

Table 5. Impact of Neutral and Negative Sentiment with control variables.

This table presents the regression results of the following equations: Left hand side: $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Neutral\ Sentiment\ i,t + \beta 2 * Xi,t + \beta 3 * Y\ j,t$,Right hand side: $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Interaction\ Negative\ Sentiment\ i,t + \beta 2 * Xi,t + \beta 3 * Y\ j,t$, where Neutral Sentiment and Interaction Negative Sentiment, respective, is the characteristics of tweets about deal i at time t. Xi,t is variables that capture the characteristics of the deal and $Y\ j,t$ measures firm j's characteristics at time t. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Variable	Abnormal Trading Volume	
Sentiment Neutral	0.911***	
	(0.281)	
Interaction Negative Sentiment		-0.003***
		(0.001)
Deal Value, log	0.016	0.109
	(0.069)	(0.079)
Operating Cash Flow to Market Value	30.416	-54.278
	(91.800)	(108.880)
Cash to Total Assets	0.854	0.471
	(0.585)	(0.706)
Tobins Q	-0.078	-0.101
	(0.071)	(0.072)
Constant	0.203	-0.423
	(1.105)	(1.328)
N obs	45	45
R-squared	0.206	0.159
	F(5, 38) = 2.89	F(5, 39) = 2.80
Prob > F	0.0259	0.0299

5.3 Neutral Sentiment Analysis, Subjectivity and Polarity

By the fact that most of the tweets were neutral, we further analyze the impact of neutral sentiment, in the importance that Koppel, M. and Schler, J. (2006) cited.

As the sentiment classification program analyzes Polarity and Subjectivity in how much from zero to one, they are mutually exclusive and cannot be together in the same regression analysis.

Subjectivity Neutral is significant at a 5% level saying that with higher subjectivity, abnormal trading volume is 113,9% higher. The variable for Polarity Neutral states that with higher polarity, abnormal trading volume is 65,1% higher, with a significance of 1%. Hypothesis 4 saying that the higher the subjectivity and polarity, respectively, is within neutral sentiments, the higher the abnormal trading volume, is thereby found to be correct.

The aggregated result of this further analysis on neutral sentiment states that when evaluating sentiments, there is a further effect of tweets. In other words, contrary to earlier analysis, one could say that there may not be just the effect of tweets in the neutral sentiment, but that neutral sentiments are expressing either an emotion, or an opinion, having an impact. The interpretation of the results is a subject for discussion below, although neutral sentiment is not to exclude in studies concerning sentiment analysis, in stating that tweets with higher subjectivity and polarity, respectively, has an impact on abnormal trading volume.

However, subjectivity and polarity both comes from neutral sentiment, and as both variables are significant with a positive coefficient, saying that these sentiments affect AVOL positive, we cannot conclude that this is because of the neutral sentiments, or if it is because that these neutral sentiments contain polarity and subjectivity.

Table six found below.

Table 6. Impact of Subjectivity and Polarity within Neutral Sentiment

This table presents the regression results of the following equations: left hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Subjectivity\ Neutral\ i,t$, right hand side, $Abnormal\ Trading\ Volume\ j,t = \beta 0 + \beta 1 * Polarity\ Neutral\ i,t$. Where Subjectivity Neutral and Polarity Neutral, respective, is the characteristics of tweets about deal i at time t. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Variable	Abnormal Trading Volume	
Subjectivity		
Neutral	1.139**	
	(0.526)	
Polarity Neutral		0.651***
		(0.222)
Constant	0.877***	0.812***
	(0.135)	(0.115)
N obs	45	45
R-squared	0.063	0.122
	F(1, 43) = 4.70	F(1, 43) = 8.65
Prob > F	0.0358	0.0053

6 Concluding Discussion

6.1 Conclusion

We looked at twitters impact on Acquisitions deals and tested if twitter has an impact on AVOL. By running regression on different proxies for attention, we concluded that tweets in general does affect AVOL prior to announcement of acquisition transactions. Hence, investor tend to trade on rumors on twitter. This is interesting because no official statement from the companies involving the deal prior to the official announcement.

From our regression results, we reject all null hypothesis except number of tweets dummy with control variables. In contrast to Zhang (2017) and other researches we tested the neutral sentiment by examine if the polarity and subjectivity of a neutral tweet affect AVOL, which we find it to be. We conclude that the market is sensitive to rumors, in which it overreacts, in alignment with Gao and Oler (2011)

Acquisitions transaction is especially interesting in being low frequent events where a newsflash or a rumor will create shocks on trading activity, as this thesis finds. Furthermore, our findings do not support that deal or firm size impact trading activity, thereby concluding that Twitter attention according to our results almost solely is the significant impactor on trading activity.

Existing literature support our results and thereby strengthens the findings in capturing the essence of the magnitude of abnormal trading volume, thus explaining why M&A type of events gets a lot of attention. Furthermore, we believe that Twitter as a social media platform will represent a larger part of the financial news in the future. We are convinced that tweets and its sentiment will have an even bigger impact in the future as twitter continuous to grow.

What the Tweet is going on? Is what we asked ourselves. After investigating rumors impact on trading activity, we can conclude that that is exactly the question that investors ask themselves. With our findings and in line with Tetlocks (2011) work on how stale news tends to make the individual investor to overreact, tells us that the marginal investor is not rational. He does not have the official information. He overreacts and trade on the unjustified information betting it could come true.

6.2 Further Research

With the basis of our event window, it would be interesting to also investigate post announcement trading as well as benchmark the results to firms without tweets. Furthermore, it would also be interesting to measure if social media attention adds more weight to a firm that already has media attention from other traditional news outlets, possibly as a control variable.

Moreover, the interesting aspect of sentiment is that it can analyze every setting having text concerning an event. Thus, it would be interesting to see how rumors in Twitter affects investors' sentiment towards all-equity firms as well.

During our research of tweets and its sentiment analysis, we suggest that it is essential to further investigating how sentiment analysis can be more precise, so that future researches on this topic can achieve an even more consistent sentiment analysis, and possibly recognize irony and sarcasm. The technology surrounding sentiment analysis and natural language processing is developing in a rapid pace, but it is interesting with this application in real markets.

Another area in which social media attention and sentiment analysis can apply to analyze the effect on transactions is companies buying out other firms making a publicly trading firm private. In addition, it would be interesting to apply our method to emerging markets and see if one reaches similar findings.

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Appendix

1. **Sentiment Analysis using Python**

Here is a tutorial how we used the natural processing language application NLTK with python, all work with python can be reference back to Bird, Steven, Edward Loper and Ewan Klein (2009).

The first step in this process is to ensure python is running on the computer that is going to be used when performing the NLTK. You can check this by entering "python" in the command line on your computer' terminal. If python is not installed on the computer being used, it is possible to download python at their home page, se link: https://www.python.org/

NLTK requires Python versions 2.7, 3.4, 3.5, or 3.6. The next step is to download and run the NLTK on python. There is a tutorial avaible on this link: https://www.nltk.org/install.html

Type in this following command into the terminal when running python.

“Start”>”Python”,

then type:

```
import nltk from nltk,sentiment.vader import SentimentIntensityAnalyzer

from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyser = SentimentIntensityAnalyzer()

def print_sentiment_scores(sentence):

   snt = analyser.polarity_scores(sentence)

   print("{:-<40} {}".format(sentence, str(snt)))

print_sentiment_scores("After buying Flipkart, Walmart seeks allies to join its fight against Amazon in India")

After buying Flipkart, Walmart seeks allies to join its fight against Amazon in India {'neg': 0.149, 'neu': 0.629, 'pos': 0.223, 'compound': 0.0772}
```

To receive the polarity and subjectivity measurement of a tweet, we used a sentiment analysis using a NLTK 2.0.4 powered text classification process, which can tell us the polarity and subjectivity if tweets comes out neutral.