ERASMUS UNIVERSITEIT ROTTERDAM

Master Thesis

Can Negative Sentiment Score of Company-specific Financial News Predict Quarterly Earning and Stock Return?

Erasmus School of Economics
Behavioral Economics

Supervisor: **Vitalie Spinu**
Co-reader: **Georg Granic**

Author:
Jing Li (443862jl)

25 July 2017

Abstract

Combining SentiWordNet lexical resources with Harvard IV-4 psychological dictionary, this paper computes negative sentiment score from the financial news articles one-month prior to the release of the quarterly earnings announcements. Within the event study framework, this paper uses negative sentiment score to (1) predict company quarterly earnings, and (2) to predict stock return including following daily return, weekly return and monthly return after the quarterly earnings announcements were released.

Main finding of this paper is that negative sentiment score obtained from the financial news article forecasts lower company quarterly earning. The relationship between negative sentiment score is strongest when predicting weekly return, but the relationship is not significant. It seems to suggest that market prices underreact to financial news. Lastly, negative sentiment score extracted from the Wall Street Journal performs the best when predicting stock returns.

KEY WORD: financial news, sentiment score, earning, stock return, prediction

Content

1. Introduction

Financial news articles from the Financial Times or Wall Street Journal are the main sources of information for most of the stock market investors as not every one can observe the company production activities. Due to the development of informational technology and statistical techniques, such as big data, individual investors can now easily access the companies' related news. The description in the news stories can help investor deduce the situation of the company profit-generating business. After reading the news article, the investors form their own opinions. With regard to polarity, these opinions could be divided into three groups: positive, negative and neutral. Based on these opinions, the investors can form their own trading strategies, which could potentially influence the stock price in the financial markets. Financial news now are daily publication, the investors can update their information about a company on daily basis with the help of these news contents.

Recently, the role of news article in the financial market has grabbed the attention of both academic researchers and practitioners, there is a growing body of research demonstrated that the language used in financial news article can help to (1) provide novel information on company accounting earning and (2) predict the stock return in the financial market.

This paper follows the methodology of Tetlock et al. (2008), who investigate whether negative word counts from the financial news stories can predict company quarterly accounting earnings and stock returns. Although they have found a negative relationship between them, their measure is not accurate. By using negative word counts, they assumed that every negative word is equally informative. I improve this measure by assigning each negative word a negative sentiment score and then aggregate them to get daily negative sentiment score. By doing this, I can treat each negative word differently. I can identify to what extent each word shows negative sentiment.

The main finding of this paper is that this negative sentiment score can predict the company quarterly earning but I find no relationship between negative sentiment score and stock return. This is likely due to the measurement error in the calculation of the negative sentiment score and limited access to the Factiva database.

The remainder of this paper is organized as follows. Section 2 is a brief literature review of the research on investor sentiment. Section 3 discusses the data. Section 4 discusses the methodology. Section 5 presents the main results of this paper. In section 6, I will conclude, discuss the limitation of this paper and propose some directions for future research.

2. Literature Review

Extracting information from all kinds of press and their influences on stock return has been studied. Some authors focuses on the fincianl news stories. Current good news can predict positive returns in the future. (Barberis et al., 1998)

Aspired by this momentum effect, Tetlock (2007) analyzed the content from the "Abreast of the Market" colunmn in the Wall Street Journal and found the negative relationship between media pessimism and market price following a reversion to fundamentals. Tetlock et al. (2008) investigated the relationship between qualitative information in the financial news stories and the stock returns after the quarterly earnings annoucments were released. Carretta et al. (2011) analyzed how the communication of information could affect investors' behavior. They showed that before corporate news were published, the investors can only judge the type of the company event. Once the news were made publie, the content of the financial news, either positive or negative, strong or week can influence the investors' trading behavior. Uhl (2011) analyzed Reuters news articles and extracted sentiemnt from them. They conducted a vector autoregression model to test the predictability of Reuters sentiment on the Dow Jones Industrial Average stock indes. It is found that negative Reuters sentiment can better predict the change of stock index than positive sentiment. Sun et al. (2016) mined texts about all news wires, internet and social media scources and calculated a high-frequency investor sentiment. They found that there is a predicitve realtion between this measure and stock market returns as well as bonds market.

Other kinds of texts, such as twitter messages or stock message boards also grabbed a lot of attention. Werner and Frank (2004) created an algorithm to calculate the bullishness of the stock market using the Internet stock message boards. They found that stock messages have the predictive power on stock market volatility while only the small effects on the stock returns. Das and Chen (2007) used classifier algorithms together with voting scheme to extract information from the stock message boards. They found that message about tech-stocks are closely related to the stock index level, trading volumes and volatility. Zhang et al. (2012) focused on using sentiment indexes to predict futur returns. Collecting stock message boards data, they applied text classifiers to it and found that sentiment index leading to same-day positive but next day negative stock returns. Sprenger et al. (2014) used twitter message as the news sources and demonstrated that before good news the returns are much higher than that before bad news.

This paper is closely related to (Tetlock et al., 2008), who use negative word counts in the financial news to predict the companies' earnings and stock returns. Rather than use the negative word counts, I incoporate the sentiment analysis to improve the accuracy of this language measure. Im et al., (2014) concluded that there are two kinds of sentiment analysis. One is lexicon-based approach, which requires a defined lexicon resource that can be used to compute the polarity of words or phrases in the document. This method includes both the manually, semi-automatically or automatically techniques. Another one is machine learning based approach, which requires a supervised classification technique classify documents to different groups. The sentiment analysis used in this paper is lexicon-based measure. Another paper closely related to this paper is Li et al., (2014), who use Harvard IV-4 psychological dictionary and Loughran-McDonald financial sentiment dictionary as the sentiment dimension to map word patterns in the finiancial news article and stock price movements. They represents each word as a vector of sentiment dimension given by dictionary and sum up the sentiment vectors for each document. Despired by their calculation, I improve simple negative word counts measure in (Tetlock et al., 2008) by assigning each negative word show up in the article a sentiment score, which is directly obtained from the SentiWordNet library. By doing so, I can identify the small differences of each negative word.

3. Data

3.1 Data Collection

3.1.1 News Data

I concentrate my analysis on 100 companies. My financial news article data range from 1980 to 2016 and is obtained from the Factiva database. These articles are daily publication and from various publication sources including the Wall Street Journal, the Wall Street Journal Online, Business Wire, Reuters News and Financial Times. Table 1 is an example of the Apple Inc financial news article data.

News source	Relevance	Publication Date	Content	Headline
J_The Wall Street Journal	["IBM" "HPQ" "AAPL"]	1980-10-18	THE LATEST HOT TIP ON THE STREET: GET A SLICE OF APPLE COMPUTER INC. AHEAD OF THE REST OF THE PACK--BUY NAUTILUS FUND. A LOT OF PEOPLE ARE TAKING THAT ADVICE AND THE CLOSED-END INVESTMENT COMPANY IS RIDING SKY HIGH, FOUR TIMES ITS ...	NAUTILUS FUND SOARS ON ITS APPLE COMPUTER STAKE

Table 1 Apple financial news article data

The financial news article data is composed in five dimensions: news source, relevance, publication date, content, and headline. Because of the limited access to the Factiva database, content only includes the first sentence of the financial news. As I investigate a long period and collect news article from various publication, it should be enough to extract information from theses texts. The relevance is a series of companies' ticker, representing how many companies are mentioned in this news.

3.1.2 Financial Data

I get the daily stock price and number of shares outstanding data from CRSP. I get quarterly earning data and report date of quarterly earnings announcements from Compustat. I also get the market to book ratio from Datastream.

3.2 Independent variable—Daily Negative Sentiment Score

I regard each financial news article as a set of words and extract daily negative sentiment score from these articles. Figure 2 shows the complete process conducted in this paper.

I start with Harvard-IV-4 psychosocial dictionary, which consists of two categories, negative and positive word list. I assume that only words in these two word lists contain information, while others are not informative. In this paper, I filter words in the news data only with negative word list as previous studies show that negative words are more closely related to stock return.

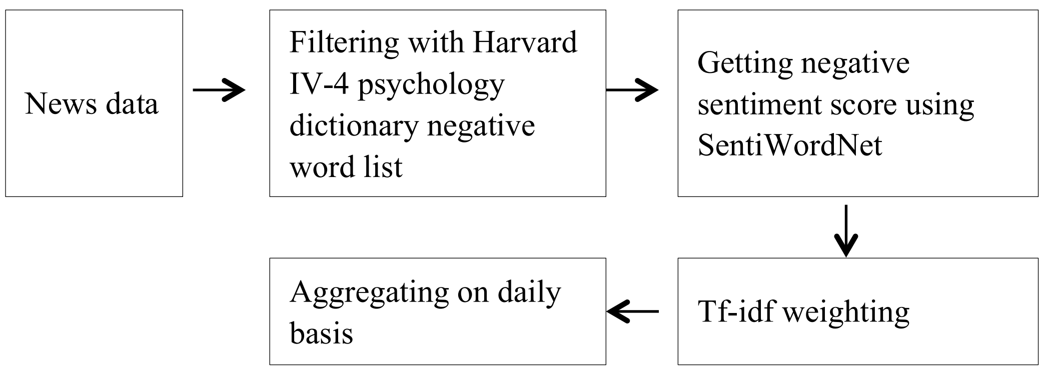

Figure 1 Complete process of calculating negative sentiment score

3.2.1 Single Word Score

I map the remaining negative words in the news data to the SentiWordNet to get the negative sentiment score for each word. SentiWordnet is a lexical resource introduced by (Baccianella, Esuli, & Sebastiani, 2010). They claimed that SentiWordNet is an improved lexical resource especially designed for sentiment analysis and opinion mining. What is closely related to SentiWordNet is WordNet, a large database for English words. Each word is shown as a series of synonyms called synsets in WordNet.[1] For example, word ‘happy’ has four synonyms (synsets) according to its different senses, ('happy.a.01'), ('felicitous.s.02'), ('glad.s.02') and ('happy.s.04'). Nouns, verbs, adjectives and adverbs are labeled for each word according to its definition. Different synsets are interlinked based on specific senses of words. This structure makes it a useful tool for computational linguistics and natural language processing. By automatically annotating all the synsets in the WordNet according to the notions of “positivity”, “negativity” and “neutrality”, we get the result in the SentiWordNet. Each synset is assigned three numerical scores, *Pos(s)*, *Neg(s)* and *Obj(s)*, which indicate to what extent this synset conveying the positive, negative or neutral sentiment. The larger the score is, the stronger the negative sentiment is. Each score ranges from 0 to 1 and three scores add up to 1. Different senses of the word thus have different scores. For example The first synset of word ‘happy’ (happy.a.01) has a positive score of 0.875, negative score of 0 and objective score of 0.125.

3.2.2 Headline/Content Score

As mentioned before, news data are composed of headline and content. Each headline and content is represented as a vector of negative words after filtering. Under the Tf-idf weighting scheme, I do weighted average for every remaining negative word in the headline/content to get the headline/content score. The formula of Tf-idf weighting scheme is shown below:

$$Tf - idf_{t,d} = tf_{t,d} \times idf_t$$

In which, tf represents the term frequency and idf represents the inverse document frequency. Tf-idf combines the term frequency and inverse document frequency together. In other words, when a negative word occurs many times in a financial news article, Tf-idf weighting scheme assigns a higher weight to it. However,

[1] What is WordNet? https://wordnet.princeton.edu/

when a word occurs in many news articles for a specified company, Tf-idf weighting scheme would assign a lower weight to it. The final weighting for a word's sentiment score is a balance of these two directions.

3.2.3 Article Score

I aggregate headline and content score together to get the article score. I give different weights to the headline and content.

$$article\ score = \frac{wh * hss + wc * css}{relevance}$$

In the equation, wh and wc represents the weights of the headline and the content, hss and css represents the sentiment score calculated from the headline and the content of the news articles. Following (Im, San, On, & Anthony, 2014), this paper applies the equal weights of 0.5 for the financial news content and headline to calculate the final sentiment score for a specified article.

Considering one article could mention several companies, I assume that articles mention only one company conveys more information than that mention several companies. The more companies they mention, the less informative to a specified company. So I divided the sentiment score by the relevance. The relevance represents the number of different companies mentioned in the certain news.

3.2.4 Daily Score

There are various news related to a particular company per day, so after calculating the article score of the financial news, I group them to together to get the daily sentiment score.

3.3 Dependent Variables

This paper uses negative sentiment score extracted from the financial news article to predict the company quarterly accounting earning and stock return.

3.3.1 Quarterly Accounting Earning

Company quarterly accounting earning is an important dependent variable in this paper. I measure it with standardized unexpected earning (SUE). I follow the formula used in (Tetlock et al., 2008), who use a seasonal random walk trend model originated by (Bernard & Thomas, 1989).

Firstly, I calculate the unexpected earning in quarter t (UE_t):

$$UE_t = E_t - E_{t-4}$$

In which, E_t represents the company quarterly earning in quarter t. E_{t-4} is the company quarterly earning in the previous year. For every unexpected earning, I conducted the standardized process. The standardization is needed if uexpected earning is not stable.

$$SUE_t = \frac{UE_t - \mu_{UE_t}}{\sigma_{UE_t}}$$

where, μ_{UE_t} and σ_{UE_t} represents the trend and the volatility of the compnay's unexpected earning, which eqaul to the mean and standard deviation of company's previous 20 quarters unexpcted earning. The calculation of the standardized unexpected earnings require that company has no missing data in the previous 20 quarters.

3.3.2 Stock Return

There are three stock returns this paper is going to predict. Figure 2 shows the exact time point those three stock returns are measured. I define the quarterly earnings announcements release day as the starting point 0. Three stock returns are daily return one-day after, weekly return one-week (5 trading days) after and monthly return (20 trading days) after the quarterly earnings announcements were released. The formulas are shown below:

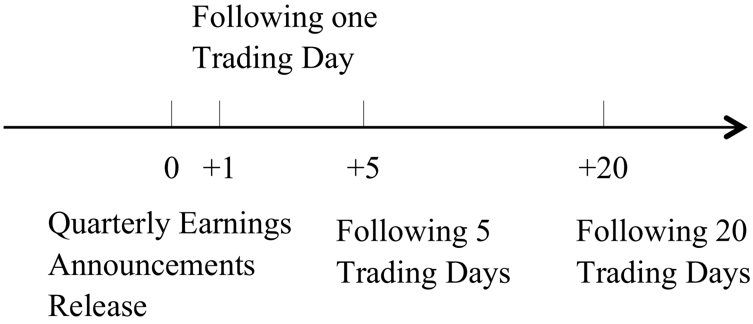

Figure 2 Future Stock Return Measuring Points

$$Daily\ Retrun: Return_{+1} = \frac{P_{+1} - P_0}{P_0}$$

Where, P_{+1} represents the stock price one-day after the quarterly earnings announcements were released, P_0 represents the stock price on the quarterly earnings announcements release day.

$$Weekly\ Return: Return_{+5} = \frac{P_{+5} - P_0}{P_0}$$

Where, P_{+5} represents the stock price on the day 5 trading days after the quarterly earnings announcements were released, P_0 represents the stock price on the quarterly earnings announcements release day.

$$Monthly\ Return: Return_{+20} = \frac{P_{+20} - P_0}{P_0}$$

Where, P_{+20} represents the stock price on the day 20 trading days after the quarterly earnings announcements were released, P_0 represents the stock price on the quarterly earnings announcements release day.

3.4 Other Control Variables

Following the event study methodology originated by (Fama et al., 1969), this paper assesses the influence from the tone of news article on the company quarterly earning and future stock return. According to (Jegadeesh & Titman, 1993), past return is an already known factor. The past winner stock, which earns higher return, also gets higher abnormal return surrounding the earnings announcement. So past return before the quarterly earnings announcements must be included as control variable.

3.4.1 Past Return

I choose [-252, -21] trading days before the release of quarterly earnings announcements release as the estimation window. I choose the [-20, +1] as the event window when predicting following daily return, [-20, +5] for weekly return and [-20, +20] for montly return as it is shown in figure 3.

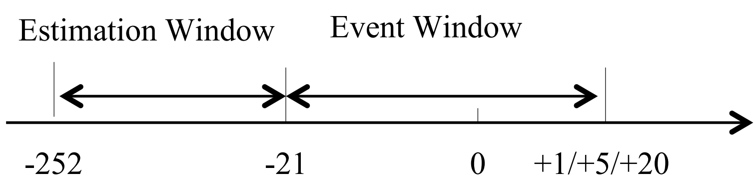

Figure 3 Estimation window and event window for past return

Abnoraml return is a common measure to represent the past return of a stock. Abnormal return is calculated as below:

$$AR_{it} = R_{it} - E(R_{it})$$

where, AR_{it} represents the abnormal return for company i in period t; R_{it} represents the return the company realized during period t; $E(R_{it})$ represents the expected return calculated from the Fama-French three factor model.

The expected return is calculated as below:

$$E(R_{it}) = \alpha_i + \beta_{i1}(R_{mt} - R_{ft}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon$$

where, R_{mt} is the market portfolio return during period t. R_{ft} is the risk-free return. SMB_t means “small minus big”, which measures the excess return of small compnies (small capitalization) over big compnies. HML_t means “high minus low”, which measure the excess return of high book-to-market ratio company over low book-to-market ratio company.

Using [-252, -21] trading days prior to the quarterly earnings announcemnts release as the estimating period, I can estimate the parameter of the Fama-French three factor model. Using these parameters I get the expected daily return during the period [-20, 0]. That is the daily return of the most recent one-month prior the quarterly earnings announcements release. The expected return for company i of time t is computed as:

$$E(R_{it}) = \widehat{\alpha_i} + \widehat{\beta_{i1}}(R_{mt} - R_{ft}) + \widehat{\beta_{i2}}SMB_t + \widehat{\beta_{i3}}HML_t$$

Combined with realized return in the past month, I get the abnormal return. as I want to control the past return $[t_1, t_2]$ surrouding the release of the quarterly earnings annoucments, the cumulative abnormal return is more appropriate. The cumulative abnormal return during the period $[t_1, t_2]$ is calculated as below:

$$CAR_{(t_1,t_2)} = \sum_{t_1}^{t_2} AR_{it}$$

In this paper, I use cumulative abnormal return ($CAR_{-30,-3}$) from 30 to 3 trading prior, abnormal return (AR_{-2}) two days prior, abnormal return (AR_{-1}) one-day prior to the quarterly eanrings annoucements were released, abnormal return ($AR_{0,0}$) on the quarterly earnings annoucements release day and bnormal return on the previous year ($Alpha_{-252,-31}$) as control variables to control for the influence from the past return. $Alpha_{-252,-31}$ is the constant in the Fama-French three factor model.

3.4.2 Size and Book-to-Market Ratio

I measure firm size as *Log (Market Capitalization)*. Market capitalization equals the price times the number of shares outstanding. I include book-to-market ratio as *Log(Book/Market)* following (Fama & French, 1992).

3.5 Data Description

This section shows some qualitative information about financial news article data and preliminary investigation on relationship between score and stock return.

Figure 4 shows the relationship between media coverage and quarterly earnings announcements release. The positive number in the x-axis represents the number of days that have passed since the last quarterly earnings announcement was released until the news article was reported. The negative number in the x-axis the number of days would occur since the news article is released until the next quarterly earnings announcement would release. The x-axis ranges from -90 to 90 days, representing one quarter. The y-axis depicts the number of news article reported. It can be seen that the news are reported surrounded around the earnings announcements release day. Most of the stories occurred on the earnings announcement release day.

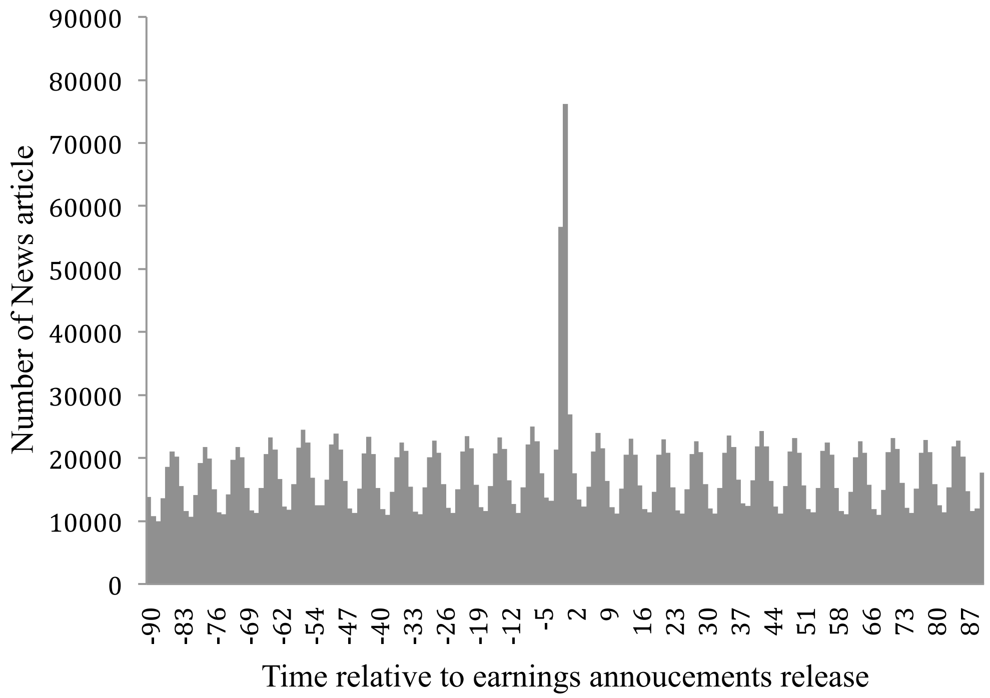

Figure 4 Relationship between media coverage and quarterly earnings announcements release

Taking Apple as an example, figure 5 shows the relationship between negative sentiment score extracted from the financial news article about Apple and its following daily return after the quarterly earnings announcements were released. The negative sentiment score is between 0 and 1 but in this case the score is relative small, which concentrated between 0 and 0.05. The highest score is 0.07. The change of the stock return is relative large, which means the stock return is volatile. The highest stock return is 23.7% and the lowest stock return is -17.2%. From the figure, it is found that the explanatory power of the negative sentiment score is weak but it really can predict the stock return at some point because there exists obvious opposite trend. Because of the large measurement error in the calculation of the negative sentiment score, it may exist a lot of noise in its final result.

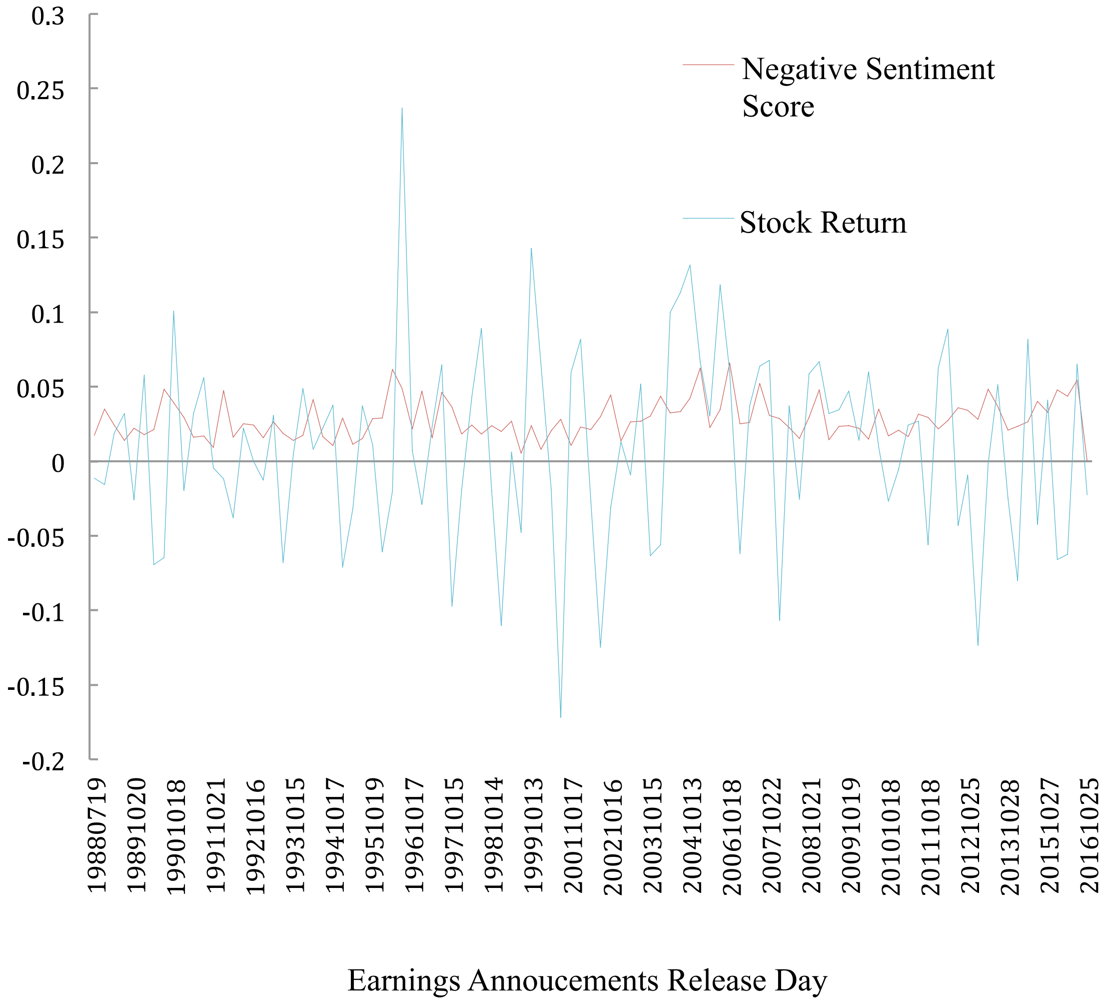

Figure 5 Relationship between stock return and negative sentiment score

4. Methodology

4.1 Predicting company quarterly earning

I use negative sentiment score to predict company quarterly accounting earning. The dependent variable is the standardized unexpected earning computed in section 3. The independent variable is the average daily score among the period [-20, -3] trading days prior to the quarterly earnings announcements release. [-20, -3] means the one-month period in the calendar date.

Other control variables include the cumulative abnormal return 3 to 20 days prior, abnormal return 2 days prior to the quarterly earnings announcements were released, the abnormal return in the past year excluding the most recent month, standardized unexpected earning lagged one quarter, log company size and log book to market ratio. The regression model is shown below:

$$SUE = \beta_0 + \beta_1 Neg_{-20,-3} + \beta_2 CAR_{-20\,-3} + \beta_3 AR_{-2} + \beta_4 Alpha_{-252,-21} + \beta_5 \log(Size) + \beta_6 \log(Book/Market) + \beta_7 lagged\ SUE + \varepsilon$$

I estimate the parameters using pooled OLS regression with clustered standard errors, following the techniques used in (Tetlock et al., 2008). The standard errors are clustered based on the calendar quarter.

4.2 Predicting stock return

I use negative sentiment score to predict company future stock returns. The dependent variable is future stock returns calculated in section 3.2.2. They are the following daily return, weekly return and monthly return after the quarterly earnings announcements were released. The independent variable, negative sentiment score is the same as that in the regression predicting company quarterly earning.

Other control variables are also similar to those in the regression predicting company quarterly earnings in section 4.1. The differences are that I add another three variables as additional control variables and delete one. The first two adding variables are abnormal return 1-day prior to quarterly earnings announcements release day and abnormal return on the quarterly earnings announcements release day. The standardized unexpected earning in this case is also included as a control variable and the standardized unexpected earning lagged one quarter is no longer included. The regression model is shown below:

$$Stock\ Return = \beta_0 + \beta_1 Neg_{-20,-3} + \beta_2 CAR_{-20,-3} + \beta_3 AR_{-2} + \beta_4 AR_{-1} + \beta_5 AR_0 + \beta_6 Alpha_{-252,-21} + \beta_7 \log(Size) + \beta_8 \log(Book/Market) + \beta_9 SUE + \varepsilon$$

The estimating techniques are the same as those used in regression predicting company quarterly earning, described in section 4.1

5. Results

5.1 Predicting quarterly earnings

This section investigates whether the negative sentiment score implied in the financial news article can provide any new insight on firm's quarterly earnings. Table 2 shows the results of the OLS regression.

In the Model 1, I only use negative sentiment score and lagged standardized unexpected earning as independent variables. It can be seen that the negative sentiment score implied in the financial news article could provide some information about the company unexpected quarterly earning. The coefficient of the negative sentiment score is -2.07. The robust t-statistics is -2.08 and it is significant at the 95% confidence level. It means the higher the negative sentiment score during most recent month before the earnings announcements are going to be released is, the lower the unexpected earnings would be reported in the quarterly earnings announcement. People can collect information about earnings announcements through the financial news articles. Apart from the sentiment score, $Lagged\ SUE$, that is, the unexpected earning of last quarter can also provide information about this quarter's earning. The coefficient of the $Lagged\ SUE$ is 0.113 and t-statistics is 5.74, which is significant at the 95% confidence level.

In Model 2, I add the most recent month stock return and the abnormal return in the past year as additional control variables. They are cumulative abnormal return in the past month, abnormal return 2 days prior to the quarterly earnings announcements release and abnormal return in the past year excluding the most recent month. I find that negative sentiment score is still significant at the 95% confidence level. The coefficient of it is -1.93 and t-statistics is -1.97. Among the newly added variables, the cumulative abnormal return during the period [-20, -3] and the abnormal return of the past year excluding most recent month have the explanatory power for the company quarterly earning. The higher past return can predict that the earning in this quarter would be higher.

In model 3, I add another two control variables. They are the company size and book to market ratio. The predictive power of the negative sentiment score decreases. The t-statistics of it is -1.51, no longer significant. The predictability of other control variables is the same as that in Model 2. Between the two added variables, the coefficient of book to market ratio is -0.121 and it is significant at 95% confidence level. The higher the book-to-market ratio is, the lower company quarterly unexpected earning. The more a company has growth opportunities, which means lower book-to-market ratio, the quicker its quarterly earning grows.

Independent variable	Model 1	Model 2	Model 3
$Neg_{-20,-3}$	-2.068 (-2.08)	-1.934 (-1.97)	-1.367 (-1.51)
$Lagged\ SUE$	0.113 (5.74)	0.108 (5.66)	0.104 (5.59)
$CAR_{-20\ -3}$		1.194 (2.19)	1.197 (2.19)
AR_{-2}		0.345 (0.20)	1.772 (0.89)
$Alpha_{-252,-21}$		121.036 (4.77)	146.400 (4.91)
$\log(Size)$			-0.006 (-0.26)
$\log(Size)$			-1.121 (-2.67)
Observations	8109	8109	7917
Clusters	143	143	143
Adjusted-R^2	-0.0005	-0.0157	-0.0280

Table 2 OLS results predicting company earning (robust t-statistics in parentheses)

Among 3 models, the earning in the last quarter can always help to predict this quarter accounting earning. The past month return is also helpful. The predictability of the negative sentiment score decreased.

5.2 Predicting stock returns

5.2.1 Predicting following daily return

Table 3 shows the regression results of using negative sentiment score to predict the following daily return after the quarterly earnings announcements were released.

In Model 1, I only include the negative sentiment score one-month prior and company quarterly earning (SUE) as the independent variables. From the sign of the coefficients, it is noted that the negative sentiment score lead to decrease in the following daily stock return after the quarterly earnings announcements were released. The coefficient is -0.006 but it is not significant. The standardized unexpected earning obtained from the quarterly earnings announcements can help to predict the following daily return. The coefficient of it is 0.0004 and it is significant at 95% confidence level.

In Model 2, past stock returns are included as control variables. There is still no relationship between following daily stock return and the negative sentiment score, but past returns can predict following daily stock return. The abnormal return on the earnings announcement release day can help predicting the return in the following day. The coefficient here is that 0.066, which means 1% increase of earnings announcement day stock abnormal return can lead to 0.07% increase of the stock return in the next day. This is significant at the 95% confidence level. While the daily abnormal return two trading days before the earnings announcements release predicts lower stock returns. The coefficient is -0.057 and it is significant at the 90% confidence level. In addition, the past year abnormal returns excluding most recent month can also help predicting the stock return. This is consistent with the momentum effect of article from Jagadeesh and Titman (1993). The coefficient of this abnormal return is 0.543, which is significant at 90% confidence level. 1% increase in the abnormal return in the past year means 0.521% increase in the stock return. There still exists a positive relationship between company quarterly unexpected earning and stock return. The coefficient of the standardized unexpected earning is 0.0003 and the t statistics is 2.62, which is significant at the 95% confidence level. The higher the unexpected quarterly earning is, the higher the following daily stock return would be.

In Model 3, I add firm size and book to market ratio as additional control varable. This is the same as the regression in (Tetlock et al, 2008) excluding share turnover. However, unlike the results in that article, there is no relationship between negative sentiment score and the following daily stock return. Other control variables' results are consistent with those in the article and the signs of all the independent variables are almost the same except the sign of the cumulative return in the past month in this paper is positive. Abnormal return on 2 trading days before the earnings announcements shows predictive power. The coefficient and its t-statistics are -0.070 and -2.39, which is significant at the 95% confidence level. The coefficient of abnormal return on the earnings announcements release day is 0.068 and it is significant at 95% confidence level. However, the abnormal return in the past year excluding most recent month is no longer significant compared to Model 2. For the company quarterly earning, the standardized unexpected earning still has the positive predictive power, which is significant at the 95% confidence level. For the company size and book to market ratio, the relationship between them and the stock return are both negative, while only book to market ratio is significant at 95% confidence level.

Among all three models, the company quarterly earning helps predicting the following daily stock return. Although the coefficient of company quarterly earning is significant at 95% confidence level, it is relative small. Between the model 2 and model 3, abnormal return two days prior and abnormal return on the quarterly earnings announcements release day have the impact on the following daily return.

Independent variable	Model 1	Model 2	Model 3
$Neg_{-20,-3}$	-0.006 (-0.68)	-0.005 (-0.59)	-0.004 (-0.47)
SUE	0.0004 (3.03)	0.0003 (2.62)	0.0003 (2.52)
$CAR_{-20,-3}$		0.0007 (0.07)	0.0008 (0.08)
AR_{-2}		-0.057 (-1.94)	-0.070 (-2.39)
AR_{-1}		-0.008 (-0.24)	-0.011 (-0.31)
AR_0		0.066 (4.13)	0.068 (4.18)
$Alpha_{-252,-21}$		0.543 (1.72)	0.372 (0.95)
$\log(Size)$			-0.0003 (-1.35)
$\log(Book/Market)$			-0.002 (-2.39)
Observations	8200	8196	8002
Clusters	144	144	144
Adjusted-R^2	-0.0130	-0.0419	-0.0537

Table 3 OLS regression results predicting stock return (robust t-statistics in parentheses)

5.2.2 Predicting weekly return

Table 4 shows the regression results of using negative sentiment score to predict the most recent weekly return after the quarterly earnings announcements were released.

When using negative sentiment score predicting weekly return. I gradually add control variables as what I do in section 4.3.1. The predictability power of negative sentiment score on stock return has improved compared to the regression predicting following daily return, but there still exists no significant relationship. The results about other control variables are similar to the results in 4.3.1. Only the abnormal return 2 days prior and abnormal return on the quarterly earnings announcements release have the impact on the weekly stock return. The company size and book-to-market ratio in this case have no influence.

Independent variable	Model 1	Model 2	Model 3
$Neg_{-20,-3}$	-0.220 (-1.49)	-0.021 (-1.41)	-0.022 (-1.44)
SUE	0.0007 (2.82)	0.0007 (2.81)	0.0007 (2.74)
$CAR_{-20,-3}$		-0.008 (-0.52)	0.014 (-0.83)
AR_{-2}		-0.167 (-4.54)	-0.152 (-3.57)
AR_{-1}		-0.085 (-2.16)	-0.084 (-2.20)
AR_0		0.049 (2.06)	0.044 (1.88)
$Alpha_{-252,-21}$		-0.050 (-0.10)	-0.216 (-0.33)
$\log(Size)$			-0.0003 (-0.58)
$\log(Book/Market)$			-0.0003 (-0.33)
Observations	8193	8189	7995
Clusters	144	144	144
Adjusted-R^2	-0.0123	-0.0405	-0.0557

Table 4 OLS regression results predicting weekly return (robust t-statistics in parentheses)

5.2.3 Predicting monthly return

Table 5 shows the regression results of using negative sentiment score to predict the monthly return after the quarterly earnings announcements were released.

When using negative sentiment score predicting monthly return, I gradually add control variables as what I do in section 4.3.1. The predictability power of negative sentiment score on stock return also has improved compared to the regression predicting following daily return, but it is weaker than predicting weekly return. The coefficient of the negative sentiment score is not significant. The standardized unexpected earning calculated from the company quarterly earning announcements still has the predictive power for the following monthly return.

Independent variable	Model 1	Model 2	Model 3
$Neg_{-20,-3}$	-0.026 (-0.91)	-0.026 (-0.90)	-0.031 (-1.06)
SUE	0.0009 (2.28)	0.0009 (2.20)	0.001 (2.55)
$CAR_{-20,-3}$		0.017 (0.38)	0.051 (1.22)
AR_{-2}		0.017 (0.12)	-0.138 (-1.28)
AR_{-1}		-0.082 (-1.04)	-0.047 (-0.52)
AR_0		0.065 (1.51)	0.045 (1.03)
$Alpha_{-252,-21}$		0.153 (0.08)	0.564 (0.30)
$\log(Size)$			-0.02 (-1.18)
$\log(Book/Market)$			0.002 (0.43)
Observations	8140	8136	7945
Clusters	144	144	144
Adjusted-R^2	-0.0136	-0.0480	-0.0597

Table 5 OLS regression results predicting monthly return (robust t-statistics in parentheses)

5.3 Predicting stock returns on sub groups

In this section, I divided the news article into different groups according to its source, the Wall Street Journal (WSJ), the Wall Street Journal Online (WSJ Online), Financial Times, Reuters news and Business Wire. I run regression on these sub groups again. Among all the sub groups, the negative sentiment score performs the best when it is computed based on news article from the Wall Street Journal. While other regression results are similar to the results when score is computed based on news article from the Wall Street Online. Therefore, only the regression results using the WSJ and WSJ Online are shown in table 6.

Model 1 and 2 use news articles from the WSJ while Model 3 and 4 use news article from the WSJ Online. I regress following daily return on the negative sentiment score as what I do in section 4.3.1. Although the relationship between sentiment score and stock return is stronger when predicting the weekly with all stories, the score from the WSJ performs the best when predicting following daily return. So the results in the table are the regression results predicting following daily return.

Independent variable	WSJ		WSJ Online	
	Model 1	Model 2	Model 3	Model 4
$Neg_{-20,-3}$	-0.011 (-1.17)	-0.012 (-1.24)	-0.002 (-0.16)	-0.002 (-0.17)
SUE	0.001 (3.83)	0.001 (3.77)	0.001 (3.44)	0.001 (3.17)
$CAR_{-20,-3}$		0.006 (0.5)		0.027 (1.59)
AR_{-2}		0.00004 (0.00)		0.042 (0.73)
AR_{-1}		0.024 (0.31)		0.129 (0.96)
AR_0		0.073 (2.57)		0.099 (2.97)
$Alpha_{-252,-21}$		0.773 (2.24)		1.359 (2.62)
Observations	3760	3760	2476	2476
Clusters	104	104	42	42
Adjusted-R^2	-0.0141	-0.0562	-0.0429	-0.1476

Table 6 OLS regression results predicting stock returns on sub groups (robust t-statistics in parentheses)

Model 1 uses WSJ news articles as dataset and only includes the negative sentiment score and company quarterly earning as the independent variables. The coefficient of negative sentiment score is -0.011 and t-statistics is -1.17. This result is better than that from all stories regression predicting following daily return. Model 2 adds other control variables used in previous section to it. As the influence from the company size and book-to-market ratio is relative small, as shown in previous section. The control variables only include the past month stock return. Abnormal return on the earnings announcements release day and abnormal return in the past year excluding most recent month can predict the following daily return.

Model 3 uses WSJ online news articles as dataset and only includes the negative sentiment score and company quarterly earning as the independent variables. The coefficient of negative sentiment score is -0.002 and t-statistics is -0.16, which is the smallest. Other results are similar to Model 1 and 2, the coefficients of abnormal return on the earnings announcements release day and abnormal return in the past year excluding most recent month are significant at 95% confidence level.

To conclude, among all the regressions above, the sign of the negative score is constantly negative. It seems suggesting that currently bad news can lead to the future decrease in the stock return. The predictive power of the negative sentiment score has improved when predicting weekly return after the earnings announcements were released. It seems implying that the information in the financial news article needs time to process and spread. People need a period of time to form their own opinion after reading the news. So, the information cannot reflect in the current stock price. Another finding is the predictability of the abnormal return 2 trading days prior to and abnormal return on the earnings announcement release day. The coefficients of these two variables are significant at 95% confidence level. The company quarterly earning can also help predicting future stock return, whatever predicting following daily return, weekly return or even monthly return.

6. Conclusion

This paper extracts sentiment score from financial news articles occurred one-month before the quarterly earnings announcements were released and investigate whether these negative sentiment score can provide information to the company quarterly earning and predict stock return.

Firstly, this paper computes sentiment score from the financial news articles. Using Harvard IV-4 psychological dictionary, I filter the words in the financial news article headline and first sentence of the content to keep only the negative words that belong to the negative word list in the dictionary. Then, using the SentiWordNet library, I get the negative sentiment score about these words and then weighted headline and content remaining words with Tf-idf weighting scheme to improve the accuracy of the calculation. Grouping all the news occurred on the same, I get the daily negative sentiment score.

Secondly, following the event study methodology, this paper uses pooled OLS regression to investigate the predictive power of negative sentiment score on company quarterly earning and stock return. For the regression predicting company quarterly earning, I control the predictability from company last quarter earning and past-month return. For the regression predicting stock return, I control the influence from the company quarterly earning and past month stock return. I use negative sentiment score to predict the following daily return, weekly return and monthly return after the quarterly earnings announcements were released. I also divided news article dataset into sub groups according to its source to test which news publication better help predicting stock return.

The main result of this paper is that negative sentiment score obtained from the financial news articles can predict the company quarterly earning. There exists a negative relationship between them. By reading these news articles, people can collect information about the quarterly earnings announcements of the companies. However, different from previous study, this paper does not find significant relationship between news sentiment score and the stock return, but the results of the other control variables in the regression have the similar results as previous study. In addition, there indeed exists some opposite trend at some points that we can observe in the figure 4. So the insignificant result is likely due to the limited access of the financial articles and the coarse sentiment score measure.

Another result is that the relationship between negative sentiment score and stock return is strongest when predicting weekly return. It is likely that market prices underreact to financial news stories, so the information from the financial news article cannot reflect in the stock prices rapidly. Lastly, when dividing the financial news article into sub groups according to their publication source, the negative sentiment score extracted from the Wall Street Journal can better predicting the stock return.

There are two main limitations in this paper. Firstly, The calculation of the negative sentiment score in this paper is simple and coarse. I do not take the definition of the word and the structure of the sentences into consideration. I just simply aggregate the negative score of all the different senses of a word. So, it is likely that some of the definition does not fit the meaning in the sentence. I also do not identify any negation structure in the sentence. Secondly, for the financial news article, this paper only gets limited access to the Factiva database. So, this paper only analyzed the headline and the first sentence of the news stories rather than the whole story. Because of the incomplete information in the news article, the identification of the tone of some news stories may be incorrect. Future research can focus on the improvement of this sentiment measure and find more complete financial news data.

Reference

Barberis Nicholas, Shleifer Andrei, & Vishny Robert. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49, 307-343.

Bernard L. Victor, & Thomas K. Jacob. (1989). Post-earnings-announcement drift: Delayed price response or risk premium. *Journal of Accounting Research*, 27, 1-36.

Carretta Alessandro, Farina Vincenzo, Martelli Duccio, Fiordelisi Franco, & Schwizer Paola. (2011). The impact of corporate governance press news on stock market returns. *European Financial Management*, 17(1), 100-119.

Das R. Sanjiv, & Chen Y. Mike. (2007). Yahoo! for amazon: Sentiment extraction from small talk on the web. *Management Science*, 53(9), 1375-1388.

Fama F. Eugene, Fisher Lawrence, Jensen C. Michael, & Roll Richard. (1969). The adjustment of stock prices to new infromation. *International Economic Review*, 10(1), 1-21.

Fama, Eugene French, & Kenneth R. French, (1992) The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene Frcnch, & Kenneth R. French. (1993) Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Im Li Tan, San Wai Phang, On Kim Chin, & Anthony Patricia. (2014). Impact of financial news headline and content to market sentiment. *International Journal of Machine Learning and Computing*, 4 (3), 237-242.

Jegadeesh, Narasimhan, & Sheridan Titman, (1993) Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91

Li Xiao dong, Xie Hao ran, Chen Li, Wang Jianping, & DengXiaotie. (2014). News impact on stock price return via sentiment analysis. *Knowledge-Based Systems* , 69, 14-23.

Sprenger O. Timm, Sandner G, Philipp, Tumasjan Andranik, & Welpe M. Isabell. (2014). News or noise? Using Twitter to indentify and understand compnay-specific news flow. *Journal of Business Finance & Accounting*, 41 (7&8), 791-830.

Sun Licheng, Najand Mohammad, & Shen Jiancheng. (2016). Stock return predictability and investor sentiment: A high-frequancy perpective. *Journal of Banking and Finance*, 73, 147-164.

Tetlock C. Paul. (2007). Giving content to investor sentiment: the role of media in the stock market. *The Journal of Finance*, 62 (3), 1139-1168.

Tetlock C. Paul, Saar-Tsechansky Maytal, & Macskassy Sofus. (2008). More than words: Quantifying language to measure firm's fundamentals. *The Journal of Finance*, 9 (3), 1437-1467.

Uhl Matthias W. (2011). Reuters Sentiment and Stock Returns. *The Journal of Behavioral Finance,* 15, 287-298.

Werner Antweiler, & Frank Z. Murray. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, 59, 1259-1294.

Zhang Ying, Swanson E. Peggy, & Prombutr Wikrom. (2012). Measuring effects on stock returns of sentiment indexes created from stock message boards. *The Journal of Financial Research*, 19, 79-114.