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How Mood Affects The Stock Market: Empirical Evidence From Chinese Microblog

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Abstract:

With the advent of the Web2.0 era, social media can achieve the rapid transmission of information and reduce the information asymmetry. In our study, we selected social media of Sina Weibo because of its wide use in China. Through text mining technology, this paper we extracted total 22504 tweets related to real estate industry. We succeeded in classify microblog accounts and two clusters of social media users are selected: individual investors and official media. Based on two dimensions of attention and emotion, this paper discusses the influence of different users on the stock market. Interestingly, the empirical results show that (1) there is an inverse U-shaped curve between attention and stock return for both official media and investor which support the over-attention underperformance hypothesis. (2) We also find that both daily sentiment of official media and investor are positively correlated to stock return. Our study contributes to a better understanding of emotion and stock market, particularly based on Chinese microblog.

Key words:

Text mining; Sina Weibo; Sentiment analysis; Stock market

1 Introduction

The growing popularity of social media encourages more and more users to participate in various online activities and produces data in an unprecedented rate. The use of social media provides the opportunity to extract data in a rapid and inexpensive manner, which means people could be addressed by more complete information (Tang et al.,2017). Chinese microblog is a new social media platform in the Web2.0 era. Internet users express and exchange their feelings such as happiness, anger and so on, through microblogs. The large amount of microblog data is a useful and timely source that carries massive sentiment and opinions on various topics (Tang et al.,2013). Through the analysis of emotional information, it not only contributes to certain business value, but also will affect stock market (Zhang,2012).

In recent years, more and more researchers focus on social media and provide methodologies to extract and process the unstructured data from social media, such as opinion mining (Kim and Hovy,2006;Ma and Wan,2010;Liu,2012;Zhou et al.,2016). Scholars began to explore the relationships between social media and stock market. There are mainly two aspects focused in literature. The first concentrates on the effect of attention. People usually have limited information-processing capacity and consequently make their decisions under time pressure (Gabaix et al., 2003). The speed of information diffusion is associated with the level of attention. Quick information diffusion allows people to take instantaneous trading action (Leung,2014).

There has been media attention (Fang and Peress, 2009; Gentzkow and Shapiro, 2010) and investor attention (Hou et al., 2007; Leung, 2014; Song, H and Bing, 2014) in literature. The official media plays an important role in the process of determining which issues would receive low or high attention by public. How much attention do investors pay to information also could affect stock market return (Dellavigna and Pollet,2009;Li and Yu,2010;Vozlyublennaia,2014) and trade volume (Seasholes and Wu,2007;Yuan et al.,2008). Second, social media provide a increasingly popular platform for individuals to share their opinions and show mood states. From a perspective of behavioral finance, researchers have shown that the stock market can be driven by emotions of market participants.

Based on previous study, we conduct our research work from four aspects. Firstly, in our study, we classify microblog accounts into several clusters and clusters of social media users which are of more interest are selected as our research object: individual investors and official media. Secondly, some investigators pay much attention to the importance of investor attention for stock return (Dellavigna and Pollet,2009;Li and Yu,2010;Andrei and Hasler,2015) ,others emphasis the importance of more media attention (Rao et al.,2010;Zhang et al.,2012;Legge and Schmid,2015), so we the examine both types of attention in the paper. Thirdly, although, it has been shown that the stock market can be influenced by emotions of investors in literature, we also analyze the official media sentiment. Individual investors tend to be more sensibility while official media are always neutral. However, it is inevitable for journalists to mix with the subjective factors when publish reports.

2 Theoretical background

2.1 Attention and stock market

Limited attention has been analyzed in a variety of economic settings, its relationship with financial markets is also should be well understood (Seasholes and Wu,2007;Dellavigna and Pollet,2009;Hirshleifer et al.,2010;Zhi et al.,2011). There is evidence that investors shift their limited attention to processing market-level information following an increase in market-wide uncertainty and then subsequently divert their attention back to asset-specific information (Peng et al.,2007). Hirshleifer and Teoh (2003) examine firms' choices between alternative means of presenting information, and the effects of different presentations on market prices in a market equilibrium with partially attentive investors. Such evidence suggests that intentional constraints may be a source of investor misevaluation of accounting information. From the above literature review, the existing literature mainly focuses on investor attention, in this paper, we also add official media attention. We expect to find the different influence on stock market return. The definition of attention measurement is proposed based on number of tweets every day.

2.2 Emotional contagion and social interaction

Emotional contagion has been defined as "The tendency to automatically mimic and synchronize expressions, vocalizations, postures, and movements with those of another person and, consequently, to converge emotionally (Hatfield et al.,1993). Emotional states can be transferred to others via emotional contagion, leading people to experience the same emotions without their awareness (Kramer et al.,2014). As a consequence of emotional contagion, two social processes, selection and influence, are proposed to explain the phenomenon (Lewis et al.,2012): people befriend others who are similar to them (Mcpherson et al.,2001), or they become more similar to their friends over time. Similar studies can be found evidence for emotional contagion on the social media. Tang et al. (2013) investigated that social relations can help sentiment analysis by proposing a Sociological Approach to handling Noisy and short Texts for sentiment classification. Different from texts in traditional media, microblog texts are noisy, short, and embedded with social relations. Sina Weibo provides three types of user interactions：repost，praise and comment around a single tweet (Tianyi et al.,2016).

3 Hypotheses

3.1 Relationship between attention and stock return

An increasing amount of research has been focused on the media-effect on the stock market because the media provides constantly information among public. Given the influence of news media, the empirical conclusion in most literatures is that media coverage of listed companies will promote people's preference for stock investment, or the rise of stock prices. Chen et al. (2007) show that the media attention on the capital market is mainly reflected in the stock price. However, too much media attention will surely make the value of the stock overestimated (Huberman and Regev, 2001). Xing and Anderson (2011) use three proxies for the cross-sectional variations in public firm-specific information and a large sample, and find an inversely U-shaped relation between synchronicity and public information.

Investor attention is the premise and objective condition of market reaction. However, limitations of time and professional skills make investor attention a scarce resource (Kahneman,1973). Dellavigna and Pollet (2009) compare the response to earnings announcements on Friday, when investor inattention is more likely, to the response on other weekdays. Results support the fact that post-earnings announcement drift based on under reaction to information caused by limited attention. Zhi et al. (2011) use search data provided by Google as an index of investors' attention, and find that the rise in investor attention can push up stock prices in the short term. Aouadi et al. (2013) find that Google search volume is a reliable proxy of investor attention. Interestingly, we show that investor attention is strongly correlated to trading volume and is a significant determinant of stock market illiquidity and volatility. Thus, modern society’s well-developed social media work as an attention-allocation mechanism, which can gain investors’ maximum attention.

Current research show that stocks with media coverage or investor attention will lead to attention-driven buying (Klibanoff et al., 1998) and overtrading. “Attention driven buying behavior” means that the attention of the market participants are easily affected by the media, thus forming “excessive attention” (Chan, 2003), and they will buy more attention-grabbing stocks. Such excessive attention will cause people’s overreaction to new information and overestimation of stock value in the short term (Daniel et al.,1998) and long term reversal of subsequent earnings, called “over attention underperformance” (Hong and Stein,1999). This paper attempts to examine whether the impact of attention on stock market returns gradually disappear after the concentration rise to be a certain degree, which is basically consistent with the “over-attention underperformance hypothesis”. Therefore, the following hypotheses are established.

H_{1a}: There is an inverse U-shaped curve between media attention and stock return.
H_{1b}: There is an inverse U-shaped curve between investor attention and stock return.

3.2 Relationship between sentiment and stock return

Emotion was the felt tendency toward anything intuitively appraised as good, or away from anything intuitively appraised as bad (Arnold,1960). Elster (1998) defined emotion as a physiological state of arousal triggered by beliefs about something. A large body of literature shows that a person's current emotional state may influence financial decision making (Hermalin and Isen,2000). Lo and Repin (2002) studied the physiological characteristics of professional stock traders and find that emotion can affect a trader's ability to survive in financial markets. So it is therefore reasonable to assume that the public sentiment can affect stock market values as much as news. Different sentiment measures have been proposed in order to forecast share returns, such as *investor and consumer surveys* (Qiu and Welch,2004;Lemmon,2006;Akhtar et al.,2012) , *trading volume* (Yuan et al.,2008), or *market volatility* (Whaley, 2000). In this study, we use mood levels as proxy for the investors' sentiment (Lamont et al.,2007;Bollen et al.,2011;Nofer and Hinz,2015;Zhang et al.,2016). The formula of daily mood index is in Section 4.

H_{2a}: The increased daily mood index on media will have positive effect on stock return.
H_{2b}: The increased daily mood index on investor will have positive effect on stock return.

4 Methodology and data

4.1 Measurement

The existing literature mainly focuses on investor attention, in this paper; we also add official media attention. The definition of attention measurement is proposed based on number of tweets every day. Based on study of Antweiler and Frank (2004), we established a daily mood index for both investors and official media. Let the number of tweets related to "positive" mood be $M_t^{positive}$, similarly, set the number of tweets related to "negative" mood be $M_t^{negative}$, the calculation of *DMI* (daily mood index) is shown as follows. If the DMI is greater than 0, it indicates that the positive signal is delivered as a whole on that day. Moreover, the larger the value, the more positive sentiment the twitter delivers. On the country, if the *DMI* is small or less than 0, it indicates that the negative signal is delivered as a whole on that day.

$$DMI = Ln\left(\frac{1 + M_t^{positive}}{1 + M_t^{negative}}\right) \tag{1}$$

The intraday stock return is calculated using following formula. Where $PRICE_{it}$ is the close price of stock i on a given day t, Where $PRICE_{it-1}$ represents the close price on the given day $(t-1)$.

$$RETURN_{it} = Ln(PRICE_{it}) - Ln(PRICE_{i,t-1}) \tag{2}$$

Finally, we control for a number of variables. Table 1 provides our descriptions.

Variables	**Definition**
Controls	
TRAVOL	The daily trade volume per stock
CURRENCYVAL	The daily stock currency value per stock
BOOKTMARKET	Book to market ratio monthly per stock
RETURNTOTALA	Return on total assets monthly per stock
LEVERGE	Total liabilities to total assets monthly per stock

RETURNNETA	Return on net assets monthly per stock
EARNINGS	Earnings per share monthly per stock
TOBINQ	The ratio between a physical asset's market value and its replacement value monthly per stock
Study Variables	
RETURN	The return of stock on a given day per stock, see formula above
ATTENTION	The number of tweets released by each investor or media each day
DMI	The sentiment delivered by per tweet

Table 1 Variables definition

4.2 Sample and data

4.2.1 Data Collection

In many parts of the developed world, the real estate industry has become the symbol of wealth creation which can foster local economy (Brown and Flynn,2008). Real estate companies are important sectors in the economy (Kummerow and Lun,2005). In China, there are many social media platforms for people to express their opinions, such as Sina Weibo; Renren (which is more like Facebook) and so on. Compared with the other alternative ways, microblog has also some advantages over those. First, it must pay attention to something both adults users as well as youngsters users. Second, many financial reviewers and famous economists and stock market commentators have microblog accounts (Danfeng et al.,2016). We have collected data from following ways.

Web data. In order to extract data from Weibo, we have to use the method of web site crawling. Based on the existing data crawling method, this paper designs customized web crawling. In this study, we use software called "Octopus Collector"[1] to capture massive weibo data. The microblog contains 8 parts:"microblog_content","microblog_author","author_id","microblog_time","comment_count", "repost_count", "praise_count" which are needed for further research. In a sum, we have extracted 22504 tweets from Sina weibo during the period from October 2015 to December 2015.

4.2.2 Identity classification

When it comes to gather microblog accounts, the subjective microblog accounts come from users who have different backgrounds, work, gender, etc. Objective microblog accounts mainly include the official media, such as "Sina Finance", "Sina sports", "Beijing News" and so on (Danfeng et al.,2016). Two clusters of social media users are of most interests: individual investors and official media. We find that "individual investors" pay more attention to the stock market, including stock movements, stock recommendation and shareholdings; "Official media" are more obvious which we can justify from their title, such as "Sina Real estate ","Live News"," 24 Hours News ","Guiyang Leju" ,etc. At the beginning, a explorative based method is used to obtain users from Weibo. The heuristic rules include whether a user publish messages containing keywords: a company abbreviation such as "Vanke ", Greenland Group" and " Poly Real Estate". After obtaining the tweet, a propagation is performed to get

[1] Octopus data acquisition system based on distributed cloud computing platform can obtain amounts of data in a very short period of time, from various web sites. It can handle extremely large-scale Web crawling tasks and achieve automatic data acquisition, editing, standardization which make us get rid of dependence on manual collection of data, thereby reducing the cost of access to information, improve the efficiency of data collection.

more users. Then two assistants are asked to label whether the collected users are falling into the two categories. The mutual agreement is above 90%, and use the principle of the minority being subordinate to the majority to reach on final conclusion. In a sum, we collected 8099 tweets for “individual investors” and 2313 tweets for “official media”.

4.2.3 Sentiment analysis

Scholars at home and abroad have done a lot of research in the field of emotion analysis and have made many achievements. The current research work can be divided into two ways: emotional knowledge based method and feature based classification method. Based on the method of emotional knowledge is mainly to set up the emotion dictionary or field emotion lexicon, to determine the polarity of text using a combination of emotional words or words subjective text (Pang et al.,2002;Turney,2002;Andreevskaia and Bergler,2006;Kanayama and Nasukawa,2006); method based on feature classification is mainly using machine learning methods, regarding emotional analysis as the traditional feature extraction, and making judgment (Pang et al.,2002). In our paper, we chose the method of emotional knowledge.

On the basis of emotional dictionary[2], we use manual emotional classification and automatic judgment to obtain emotional information from microblog. Emotional polarity shows that the main emotion of vocabulary is negative, positive or neutral. First, the micro-blog content is matched with the large-scale emotion corpus, so as to automatically obtain the emotion category. Then, we use manual classification method to select emotional words from the first class of selected words, and divide the emotional categories. Finally, we use emotional polarity to divide emotional micro-blog information. If the contents transfer positive signals or emotions we classified as "positive"; if the contents convey negative signal or emotions then we classified as "negative"; otherwise it is treated as "neutral". If our master students have different judgment on the same twitter, we use the principle of mode to reach on our final conclusion. In addition, we use ROST Content Mining tool[3].In particularly, the software supports adding own emotional dictionary to ensure that the result is reliable and accurate.

5 Empirical analysis

5.1 Descriptive Statistics

Table 2 provides the descriptive statistics of key variables. Our observations for investors and official media are 1371 and 712 respectively after deleting some invalid samples. The mean of DMI is positive for both investors and official media, which indicates that positive sentiment, takes the large part. The maximum and mean of attention for investor is larger than that of official media. In order to avoid multicollinearity problems, we analyze the explained variables and explanatory variables using Variance Inflation Factor method (Kutner et al.,2004). The variance inflation factor (VIF) quantifies the severity of multicollinearity in an ordinary least squares regression analysis. It provides a method that measures how much the variance of an estimated regression coefficient will change because of collinearity. The empirical judgment

[2] The emotional dictionary contains two parts: emotional words and emotional phrases, which are constructed and annotated by people. The source mainly includes microblog emotion corpus established by Zhang, S. (2012). "Sentiment Analysis of Chinese Micro-blogs Based on Emoticons and Emotional Words." *Computer Science*. .The dictionary now contains 2928 lexical entries.

[3] It was developed by a virtual study team from Wuhan University. This tool can automatically analyze sentiment of text, say if we upload the file which needs to be analyzed, and then the emotional analysis of detailed results will be automatically generated including emotional segmentation statistics, neutral emotional results and emotional distribution.

method shows that when 0 <VIF <10, there is no multiple collinearity. Our results show that the maximum VIF is 8.52, which is less than 10, that is, our variables pass the test.

Variables	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**
	Investors			**Official media**		
Controls						
CURRENCYVAL	16.36	1.18	1371	0.03	0.04	712
RETURNTOTA	0.02	0.03	1371	0.03	0.04	712
RETURNNETA	0.02	0.04	1371	2.28	12.03	712
LEVERAGE	0.98	1.62	1371	0.48	0.65	712
EARNINGS	0.36	0.53	1371	0.65	0.30	712
BOOKTMARKET	0.65	0.27	1371	2.72	3.42	712
TOBINQ	2.25	2.22	1371	16.39	1.34	712
TRAVOL	17.17	1.47	1371	16.75	1.52	712
Study Variables						
RETURN	0.01	0.05	1371	0.02	0.04	712
DMI	0.34	0.78	1371	3.07	8.54	712
ATTENTION	4.00	13.69	1371	0.15	0.49	712

Table 2 Descriptive Statistics

5.2 Empirical Results

5.2.1 Relationship between attention and stock market

By examining the linear relationships, Table 3 suggests a positive relation between attention and stock market for both investors and official media. However, the relation between stock return and attention may be certainly non-linear. To better address this non-linear effect, we add the attention-squared to investigate whether the relationship is reflected in U-shape curve and get the improved.

As is shown in Table 3, the coefficient of attention square (β= -0.21, $p<0.05$) is negative and investor attention-squared has a significant impact on stock return. Our result indicates that there is an inverse U-shaped curve between attention and stock return. Further, this shows that the impact of media attention on stock market returns gradually disappear after the concentration rose to be a certain degree. It refers to the phenomenon that stocks with no or low mass media coverage earn higher returns than stocks with high coverage even after controlling for well-known risk factors (Fang and Peress,2009;Chemmanur and Yan,2010).
Regards to investor attention, with statistical significance (β= -0.26, $p<0.001$) it also showed inverted U-shaped relationship between attention and stock return, which is consistent with the over-attention underperformance hypothesis. We can therefore accept hypothesis 1a,1b.

VARIABLES	**STOCK MARKET RETURN**			
	Official media		**Investor**	
	Model 1	Model 2	Model 3	Model4
Controls				
RETURNTOTA	5.69	5.35	-2.12	-1.99
RETURNTONA	-4.20	-3.55	1.21	1.31
LEVERAGE	-0.01*	-0.01*	-0.03	-0.03
EARNINGS	0.06	0.00	0.06	0.00
BOOKTMARKET	-0.50*	-0.47	0.05	0.12
TOBINQ	-0.15***	-0.15***	0.06**	0.06**

TRAVOL	0.06	0.05	0.07*	0.05*
CURRENCYVAL	-0.04	-0.04	-0.04	-0.03
CONS	0.29	0.27	-0.71	-0.75
Independent Variables				
ATTENTION	0.03***	0.05***	0.01***	0.03***
ATTENTION-square		-0.21*		-0.26***
N	712	712	1,371	1,371
Adj R^2	0.24	0.24	0.03	0.04
F	25.63	23.88	4.99	6.14

Table 3：Relationship between Attention-squared and Stock Market

Note: *** 、**、* Indicates statistical significance at the 0.1%, 1% and 5% leve1.

5.2.2 Relationship between mood and stock market

We further explore whether sentiment on Sina weibo is related to stock price (Table 4). We find that both media *DMI* (β=0.12, p<0.001) and investor *DMI* (β=0.05, p<0.001) have a significant positive relation to intraday stock return, indicating that positive sentiment is associated with higher stock price. This result is in line with evidence from psychology, where positive sentiment causes investors to trade more, as they look to sustain with a positive outcome. This is consistent with Siganos et al. (2014) who examine the relation between daily sentiment and trading behavior within 20 inter-national markets by exploiting Facebook's Gross National Happiness Index and find that sentiment has a positive contemporaneous relation to stock returns. We can therefore accept hypothesis 2a and hypothesis 2b.

VARIABLES	**STOCK MARKET RETURN**	
	Official media	**Investor**
	Model 1	Model 2
Controls		
RETURNTOTA	5.99	-2.38
RETURNTONA	-5.83	0.69
LEVERAGE	-0.01*	-0.03
EARNINGS	0.21	0.09
BOOKTMARKET	-0.57*	0.02
TOBINQ	-0.15***	0.05**
TRAVOL	0.06	0.05*
CURRENCYVAL	-0.02	-0.01
CONS	0.00	-1.01
Independent Variables		
DMI	0.12***	0.05***
	(3.61)	(5.57)
N	712	1371
Adj R^2	0.21	0.04
F	21.20	6.80

Table 4: Relationship between mood and the Stock Market

Note: *** 、**、* Indicates statistical significance at the 0.1%, 1% and 5% leve1.

6 Conclusion

This paper examined the relationship between one of the social media, Sina weibo and stock market. A huge number of micro blog users play an important role in the organization information transformation, in our study, we selected investors and official media. Our new findings are shown as follows. Firstly, we take into account both investors and official media's attention, the results show that there is an inverse U-shaped curve between attention and stock return. Secondly, we find that both media DMI and investor DMI have a significant positive relation to intraday stock return, indicating that positive sentiment is associated with higher stock price.

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