Asian Journal of Information and Communications 2017, Vol. 9, No. 2, 67-79

KISDI
KOREA INFORMATION SOCIETY DEVELOPMENT INSTITUTE

Asian Journal of Information and Communications

An empirical study of potential mechanism between social emotions and stock prices in China*

Jinzhao Wang**
Fudan University

Fenfen Zhou***
Third Complete Primary School of Loudi City, Hunan Province

Yahuan Dai****
Anhui University

Tong Wu*****
University of Shanghai for Science and Technology

Abstract

With the development of the Internet, all kinds of social media have become important platforms for financial market investors to share information, exchange ideas and express emotions. So we can make good use of the social media to study the emotions people express. According to the behavioral finance theory, investor sentiment will become a systematic risk that affects the equilibrium price of financial assets. So we want to study the relationship between the stock prices and investor sentiment based on the social media. In this study, we use web crawler technology based on Python to craw comments people post on the website and analyze the data by affective computing based on R. We construct an investor sentiment index based on the affective computing results and do regression with the Shanghai Composite Index to investigate the relationship between them. Considering the special features of the Chinese stock market, we take institutional investors into consideration and build a model of potential mechanism between social emotions and the stock prices in China. The study shows that investor sentiment is not the cause of the change of stock prices. On the contrary, it is the institutional investors' transaction that influences the stock market which brings about the change of investor sentiment.

Keywords: social media, investor sentiment, stock price, affective computing

1. Introduction

In today's society, social media has become an important platform for people to share information, express opinions and have discussions. For example, stock forum is a popular web community among investors. It can provide stock recommendation, stock quote analysis and even courses to teach people how to select and trade stock. It's convenient for investors to get information in time, share stock investment experience and discuss with each other on the website. According to behavioral finance theory, the stock market is not entirely effective as people are bounded rational and irrational investors exist in the market. Investor sentiment will become a systemic risk that affects the equilibrium price of financial assets. Since investors express their emotions in the stock forum, it may have something to do with the stock market. So we select a social media platform called

* This research work was supported by Shanghai Pujiang Program (No.16PJC007).
** Corresponding author: 17210690015@fudan.edu.cn
*** 412391511@qq.com
**** yahuandai@163.com
***** 956587728@qq.com

“Guba” which is a mainstream stock forum in China to analyze the social emotion and then analyze the mechanism of social emotion and stock prices by using big data analysis method and affective computing in Chinese stock market.

This paper is organized as follows. In section 2, we review the literature related to influence that emotion has on decision-making and affective computing in social media. In section 3, we introduce the research model including Web crawler technology based on Python, affective computing based on R and then we compose an investor sentiment index, compute it and do regression between investor sentiment index and stock’s rate of return. Besides, we do Granger causality test to see the causal relationship. At last,we take the institutional investor into consideration and build a model to analyze the mechanism between investor sentiment and stock prices. In section4, we show the empirical results and have a discussion.

2. Literature review

Traditional financial decision theory is based on the Efficient Markets Hypothesis, Portfolio theory and Capital Asset Pricing Model. It is believed that people’s decision-making is based on Rational Expectation, Risk Aversion, Utility Maximization and other “rational people” hypothesis. However, it’s hard to explain the Herding effect, Calendar effect and many other anomalies in the stock markets. Behavioral finance introduces the important role of emotional factors such as social emotion in financial decision-making (Prechter, 1999). Emotion refers to a subjective, direct psychological experience associated with a thing or viewpoint (Sadock, 2000). Recently, there are many researchers interested in studying the relationship between emotion and financial decision-making.

Swaminathan (1996) points out that emotion and earnings are positively correlated, when investors are depressed, the stock prices are low, on the contrary, when the investors are sentimentally active, the stock prices are high. But this effect is short-term, in the long term, the stock prices will return to the original track. Frankfurter and McGoun (2001) think that market sentiment can convey investor expectations of information, and it can explain the stock premium chain and risk-free rate of the mystery which the traditional asset pricing theory cannot explain. In the early stage, the study of the relationship between emotion and decision-making in the stock market mainly focuses on decision-making theory, which is based on the rational mathematical model and completely rejects the influence of emotion.

In China, since there are many special factors different from mature stock market, such as the stock market is imperfect, bounded rational retail investors account for a large part, many anomalies in the Chinese stock markets cannot be explained. Many researchers have studied the relationship between investor sentiment and stock prices, and have got many different results which cannot reach an agreement. Wang and Sun (2004) constructed a model to show that sentiment has significant impact on the return and volatility, and institutional investors probably are the source of noise-trading risk. Rao (2005) composed an investor sentiment index BSI based on the stock market quotation analysis of CCTV and China Securities Journal, did a regression analysis between BSI and the rate of return in stock market, and the result showed that the regression coefficient wasn’t statistically significant and didn’t have a fixed law as fluctuating between positive and negative. So there is no strong relationship between investor sentiment and stock rate of return. Quan-Hui and Meng (2010) divided a sample time into two stages between rising and descending time, made an empirical analysis on between investor sentiment and the composite index of Shanghai Stock Exchange using Cointegration test and Granger causality based on ECM. And the results suggested that there is a unidirectional Granger causality from the composite index of Shanghai Stock Exchange to investor sentiment in the whole sample time and the descending sample time. However, there is bilateral Granger causality between investor sentiment and the composite index of Shanghai Stock Exchange in rising sample time. Based on the existing study on the relationship between investor sentiment and stock prices in Chinese stock market, we cannot draw a consistent conclusion on whether investor sentiment is the source of intriguing change of stock prices or not.

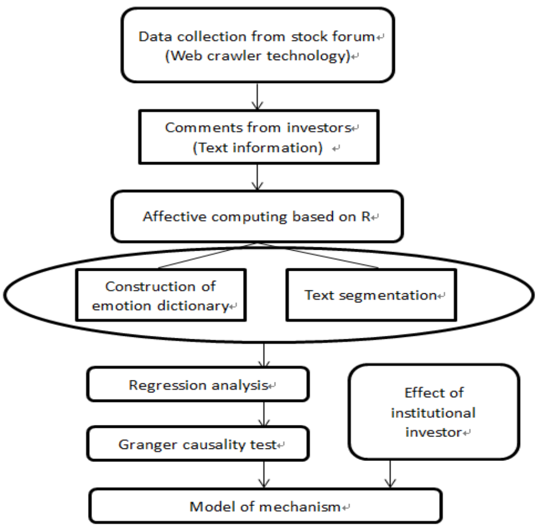
On the other hand, with the development of the Internet, the strong influence of social media on social behaviors has raised much attention (Dai et al., 2015).The famous Semantic Evaluation Conference in the field of computational linguistics SemEval set up an evaluation mission in 2007 to conduct emotional analysis of news headlines. Golder and Macy (2011) use the dictionary-based approach to do automate emotional analysis of Twitter microblogs published by millions of bloggers which come from different regions and different cultural backgrounds. The result clearly recognizes that the pattern of people's moods changes cyclically over time. Paltoglou and Thelwall (2012) use emotional rules based on the rules of Twitter and other microblogging to do emotional classification and emotional intensity analysis.

In China, Yang et al. (2012) find hot events according to the number of emotional words and the expression of emotional changes in the microblogging text. Niu et al. (2014) established emotional artificial microblogging data set including happy, sad, anger and fear, based on two commonly used emotional dictionaries C-LIWC and HowNet on the Chinese microblogging emotional analysis. However, the field of emotional analysis in the Chinese social media remains to be further researched.

3. Research model

In this study, we collect data from the website by web crawler, then clean data and extract useful information for the research. After that we analyze the useful information that is the investor sentiment and build an investor sentiment index to conduct regression with the Shanghai Composite Index to investigate the relationship between them. At last, we take into account a number of special factors in Chinese stock market and build a potential mechanism between social emotions and the stock prices in China.

Figure 1. Research framework



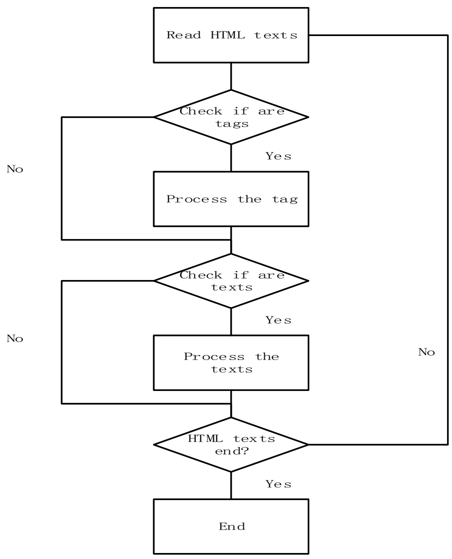
As is shown in Figure1, first, we use web crawler technology based on Python to craw comments related to stock investments from investors in the stock forum called "Guba". Second, we clean the data collected from the website and do affective computing based on R, including constructing emotional dictionary, doing text segmentation, composing an investor sentiment index and calculating it. Third, we do regression between investor sentiment index and the stock's rate of return. We use the regression analysis to estimate the relationship between the two variables. Regression analysis helps us understand how the typical value of the dependent variable that is the Shanghai Composite Index's rate of return changes when the independent variable that is the investor sentiment is varied. Then, we do Granger causality test to see the causal relationship. The Granger causality test is a statistical hypothesis test for determining whether one time series is useful in forecasting another, which can measure the ability to predict the future values of a time series using prior values of another time series. In this study, we use Granger causality to determine whether the investor sentiment is the cause of the stock's rate of return. At last, we take the institutional investors into consideration and build a model to analyze the potential mechanism between investor sentiment and stock prices.

3.1 Web crawler technology based on Python

Web crawler (also known as web spider, web robot) is a program or script that automatically crawls web information according to certain rules. Web crawler generally crawls information from the URL of one or several initial web pages to get the URL on the initial page. During the crawl of the web page, the new URL is automatically taken from the current page until the system stops. This web crawler is designed to crawl information based on the posting time of the stock, which crawls and saves all posting times in a range.

Generally, in a simple web crawler design, it only needs to initiate HTTP get or post request, simulate the user's Internet behavior, and collect the relevant web content which can be downloaded. However, a simple HTTP request in front of a large crawling task cannot meet the needs of users for data filtering, storage, multi-threaded access, so you can use a professional web crawler framework. In the experience of efficient

Figure 2. Web crawl process



program to achieve at the same time, you can also accord to the actual needs of users to expand the corresponding framework. At present, various mainstream programming languages provide a framework for implementing web crawlers. This article is based on the python sgmllib and urllib2 framework implementation. Figure 2 shows the process.

In this study, we choose a famous stock forum in China called Guba (www.guba.eastmoney.com) as our data resource because currently its number of users ranks No.1 among Chinese financial forums, the daily page view is huge and the daily number of posts and replies can reach 100 thousand. Since it can provide timely and accurate information, it attracts many stock investors to communicate in the forum, express their opinions and share their experience. Much of its active users are stock investors, so we can study the stock forum to know the sentiment of Chinese stock investors. However, the stock forum does not open the official data access API, in order to get a large number of information, we choose to use the web crawler to analyze the html code to obtain data.

In Guba, the discussion part is divided by category. There are different sub-forums related to a single stock. We chose the Shanghai Composite Index forum to collect the daily comments people post and reply related to the stock market.

In this process, we collected the daily comments posted and replied in the Shanghai Composite Index forum from January 4th, 2016 to December 31st, 2016.

3.2 Affective computing on social emotions

Emotional analysis methods are divided into two categories: One is based on the emotional dictionary and the other one is based on machine learning. The method based on the emotional dictionary needs to use a marked emotional dictionary. The method based on machine learning requires a large number of artificial annotated corpus as the training set, and the classification of emotion is realized by extracting the text feature and constructing the classifier. Since the emotional dictionary is easier to obtain than the corpus, we choose the emotional dictionary for emotional analysis.

R is a language and environment for statistical computing and graphics. R is an integrated suite of software facilities for data manipulation, calculation and graphical display. It contains a well-developed, simple and effective programming language including conditionals, loops, user-defined recursive functions and input and output facilities. In this study, we use R as a tool to do text segmentation.

3.2.1 Construction of emotional dictionary

In this study, the emotional dictionary plays a very important role. Due to the characteristics of network commentary language: timeliness, domain and non-normative, the artificial construction of the dictionary needs to consider comprehensive and dynamic update. In this study, we filtrate and update the targeted dictionary purposefully. In particular, we have joined the financial industry vocabulary to increase the hit rate in the category. There will be a big difference in the frequency of certain words in different industries, and these words may be one of the keywords of emotional classification.

(1) The choice of basic dictionary

The existing Chinese emotional dictionary mainly includes the Chinese emotional polarity dictionary NTUSD, the emotional body vocabulary of Dalian University of Technology, the “Emotional Analysis Letters (beta)” published by Taiwan University, and the Open Source “Synonyms”. After comparison, in this subject, we choose Dalian University of Technology emotional dictionary library.

(2) The construction of dictionary in the field of finance

In this paper, we use the commonly used securities operating vocabulary, extract the words with emotional tendencies, and construct an emotional dictionary in the field of stock investment. In order to improve the accuracy of emotional analysis process, we also select a certain size of the stock commentary corpus, extract the emotional polarity words for artificial labeling, which also joined the domain dictionary.

(3) The construction of network language dictionary

With the rapid spread of social media, people are increasingly involved in the Internet's comments, followed by the emergence of a large number of new network terms used to express people's emotional tendencies. Therefore, we need to add the frequently-used network language with emotional tendencies into the emotional dictionary to do the network comment information emotional analysis.

3.2.2 Affective computing algorithm

(1) JiebaR Chinese text segmentation package

We use JiebaR Chinese text segmentation package. The R version of Jieba supports four kinds of segmentation model including Maximum Probability, Hidden Markov Model, Query Segment and Mix Segment. Maximum Probability Model constructs the directed acyclic graph and carries on the dynamic programming algorithm according to the Trie tree, and it is the core of the word segmentation algorithm. Hidden Markov Model uses HMM Model based on the China Daily et al. corpuses to do text segmentation. The main idea of the algorithm is based on (B, E, M, S) four states to represent the hidden state of each word. HMM Model is provided by dict/hmm_model.utf8. Segmentation algorithm is Viterbi. Mix Segment provides the best text segmentation effects among the four models above. It combines Maximum Probability Model and Hidden Markov Model. As for Query Segment, it uses mixed model to segment text first, and then, as for the long words, it will list all possibilities that it may become a word and find whether it is in the dictionary or not.

JiebaR can do the part of speech tagging, keyword extraction and text Simhash similarity comparison at the same time. It supports Windows, Linux operating system, and it can load multiple word system simultaneously through Rcpp Modules, thus you can use different text segmentation and thesaurus. Besides, it supports a variety of text segmentation, Chinese name recognition, keyword extraction, part of speech and text Simhash similarity comparison and other functions. And it can support the loading of custom user thesaurus, set word frequency, part of speech. At the same time, it supports Simplified Chinese, Traditional Chinese word segmentation, and automatic judgment coding mode.

Compared with the existing word segmentation tool, we take into account the accuracy and ease of use of text segmentation, and finally choose Jieba Chinese text segmentation as our text segmentation tool. In this study, the default text segmentation model is adopted, and the implicit Markov model (Hidden Markov Model) and the user custom lexicon method are adopted.

Table 1. An example of text segmentation

```
Library (jiebaR）
Library (jiebaRD)
Sentiment_dataset<-read.csv("D\\R_language\\test.csv")
Mytext<-"今天我很开心" ("Today I'm happy")
Mywork=worker()
Segment_result<-(myworker<=Mytext)
```

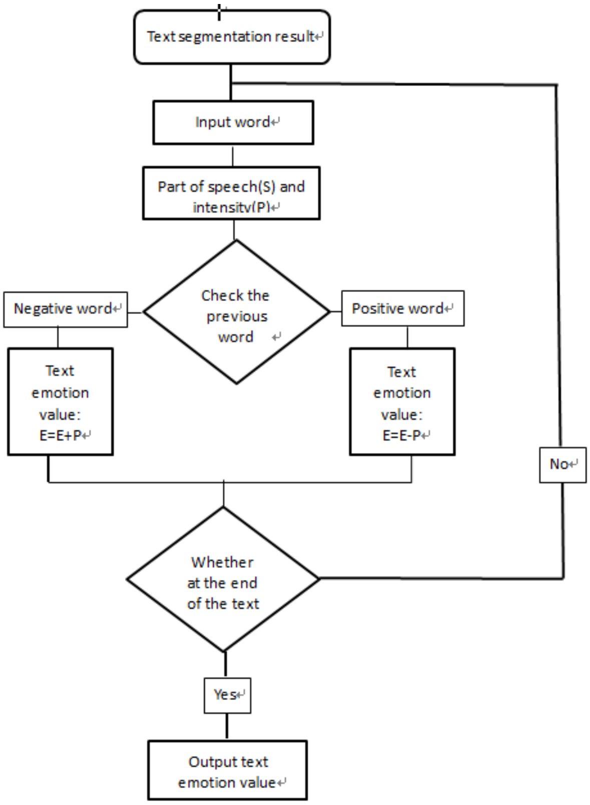
Output: "今天(today)", "我(I)", "很(very)", "开心(happy)".

(2) Chinese text affective computing algorithm

First, read the emotional dictionary. Get the list of commons, the list of derogatory words, the list of neutral words; get the list of emotional classification words and their emotional intensity. Second, read the text to be analyzed. Third, do Chinese text segmentation. Next, extract the emotional words and match them with the emotional dictionary.

Find the emotional classification of each word in the sentence, read its emotional intensity, subtract the negative emotional score from the positive emotion score, and get the total score of the sentence. At the same time, respectively, calculate the total score of positive emotions and negative emotions, as for neutral emotions, treat similarly. It should be noted that there are negative words and degree adverbs in the sentence, which will affect the sentence's emotional direction and intensity, such as “do not like”, broken down into “very”, “no”, “like”, it is wrong if only count “like”, because there is “no” in the front of it, which is the opposite of emotion and there is a “very” reflecting that the degree is very strong. So it is necessary to determine whether there are negative words, if there is, we need to reverse the emotional tendencies. And we need to check whether there is a degree adverb, if there is, do weighted processing.

Figure 3. Flow chart of affective computing based on R



3.2.3 Investor sentiment index calculation

(1) Calculation of the word's emotion index

Natural language is a tool for people to express and exchange ideas and feelings, and words are the basic unit of natural language processing. The words that express emotional tendencies are often called polar words. This study divides the words that express the mood of the user into "bullish" and "bearish" terms according to the investors' attitudes towards the future securities market. In addition, there are two types of words: degree words and negative words. The degree word is to increase or weaken the ups and downs of the word, the negative word is to express the negative price of the word. After matching with the constructed emotional dictionary library, you can get the polarity of each word and intensity value.

(2) Calculation of sentence's emotion index

$$sten_i = \sum_{m=1}^{M} (-1)^s * word_{int}$$

$$\begin{cases} s = 0, if\ pol \geq 0 \\ s = 1, if\ pol < 0 \end{cases}$$

(3) Calculation of stock forum's daily emotion index

$$e_t = \frac{\sum_{i=1}^{N} sten_i}{N}$$

Table 2. Example of calculation of Chinese text emotion value

No	Text	Emotion index
1	短期内不会回调2800, 大盘会沿着这条红线上涨。 (In the short term, the index won't go back to 2800, and it will go up along the red line.)	2.85
2	A股全球领头羊, 已经确立, 给机会就加仓 (The leading A share, buy in more shares if you have the chance.)	8.33
3	今天上证高开, 就是好事, 低开不好。 (It's a good news that the index started with a high value today.)	2.72

3.3 Regression analysis

We conduct a regression between the daily investor sentiment index and rate of return of Shanghai Composite index using the data from January 4th 2016 to December 31st 2016 (244 trading days in total). However, the result is not statistically significant the correlation coefficient is low. The following charts show the results:

Table 3. Analysis of variance

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	FValue	Pr > F
Model	1	0.000242	0.000242	1.15	0.2851
Error	242	0.051070	0.000211		
Corrected Total	243	0.051310			

Root MSE	0.01453	R Square	0.0047
Dependent Mean	0.00043111	Adj R-sq	0.0006
CoeffVar	3369.59100		

Table 4. Parameter estimates

Parameter Estimates					
Variable	DF	Parameter Estimates	Standard Error	t Value	Pr > |t|
Intercept	1	-0.00133	0.00125	1.06	0.2899
Sentiment_index	1	0.000369	0.000345	1.07	0.2851

From the chart we can see that the R square is 0.0047, which means the model isn't satisfied and the change of the return of Shanghai Composite Index can hardly be explained by the investor sentiment index. Besides, the estimated parameter of the sentiment index is 0.00036942, which means the two variables have little relationship. In conclusion, we cannot use the investor sentiment index to explain the change of stock prices.

3.4 Granger causality test

To analyze the relationship between investors sentiment index and stock prices, we did a granger causality test. Before that, we did a stationary test to test whether the two variables are stationary series or not. We did a unit root test, and the result rejected the unit root (p value=0.000), which means it satisfies the station requirement of the model.

The granger causality test's result shows that, at the 5% significance level, the hypothesis "investor sentiment value ln is the Granger reason for the change of Shanghai Composite index" can be rejected and the hypothesis "the change of Shanghai Composite Index is not the Granger reason for investor sentiment value ln" can also be rejected. So it can be seen that the investor's sentiment is not the Granger reason for the Shanghai Composite index's ups and downs. In the Chinese stock market, investor sentiment does not have the predictive power to the stock prices, and does not have a systematic impact on the pricing of the assets. Social media sentiment often follows the trend of the stock prices, and it will be presented later. So it is the stock prices that induce the change of investor sentiment.

Table 5. Granger causality test's result

Null Hypothesis	Obs	F-Statistic	Prob.
ln does Granger Cause	244	2.3918	0.0421
does not Granger Cause ln	244	2.6731	0.0517

3.5 Effects of institutional investors

From the above regression and Granger Causality test, we find that investor sentiment is not the causality for the stock prices. Considering the special factors in Chinese stock market, we want to take the institutional investors into consideration and combine the two factors to find the mechanism between investor sentiment and stock prices.

3.5.1 Current situation of Chinese institutional investors

In China, institutional investors include securities investment funds, social security funds, securities companies own business, insurance companies and enterprises, etc. They focus on liquidity and prefer to invest in big-size and good-liquidity market. Trading standard commercialized investments can help them adjust investments according to latest information in time.

As an important part of the securities market, institutional investors have advantages of decision-making in size. And its decision-making has a leading effect on social investors and is more likely to induce systematic trading risk.

Figure 4. Percentage of stock shares held by institutional investors and stock prices

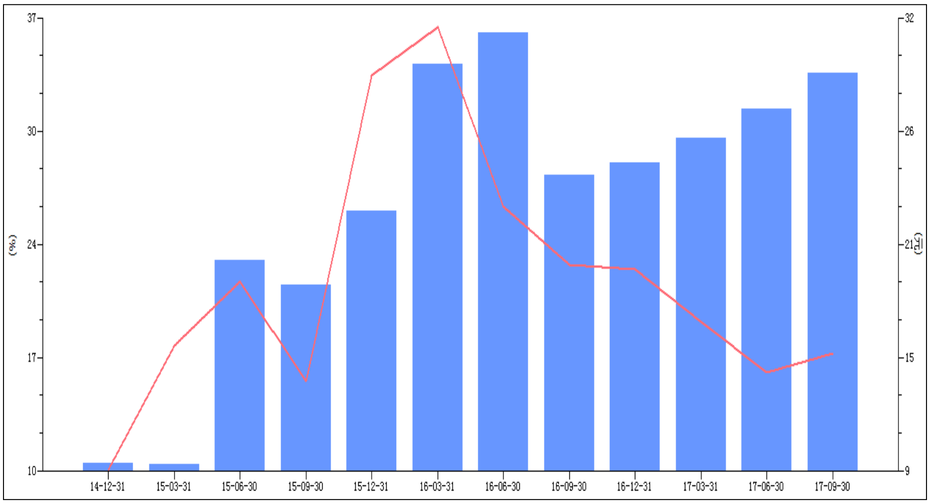


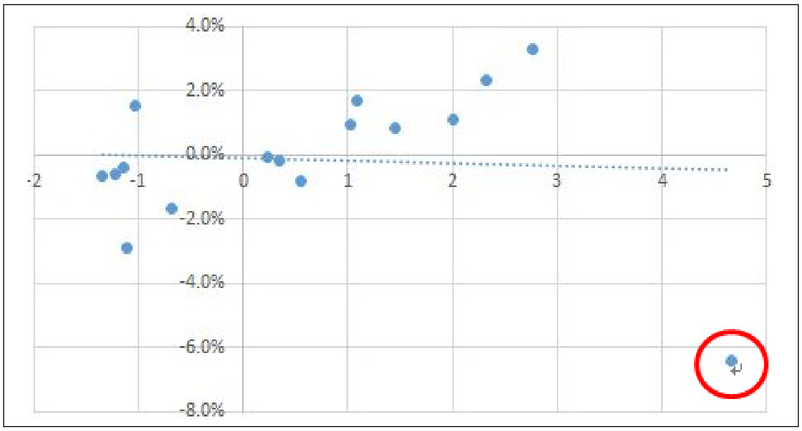
Figure 4 shows the percentage of stock shares held by institutional investors and stock prices. The histogram represents the percentage of stock shares held by institutional investors, and the graph represents the stock prices. The horizontal axis represents time from December 31st, 2014 to September 30th, 2017. The left vertical axis represents the percentage of stock shares held by institutional investors, and the right vertical axis represents the stock prices. We can see from the figure above that: (1) institutional investors account for a large part, which may have huge influence on the stock market. (2) The change trend of the two variables are pretty consistent, which indicates a potential relationship between them.

3.5.2 Case study of institutional investors' effect

Figure 5 shows the relationship between investor sentiment index and Shanghai Composite index in February 2016. The cited circle indicates abnormal phenomenon whose index is far away from the average level.

Actually, it was on February 25th, 2016, and institutional investors had a huge influence on the stock market.

Figure 5. Scatter diagram about relationship between investor sentiment index and Shanghai Composite index in February 2016



What institutional investors did on that day is as follows:

(1) Adjust deposit reservation, part of the institutions paid a larger amount of funds, multiple factors superposition made funds more difficult to borrow. Interbank funds were tightly affected by the exchange, leading to an increase in the backwash rate of the exchange. 1 day GC001 interest rate hit the highest intraday 8.5%, the highest since February 4, up 564.1% over the previous day; 2 days GC002 interest rate hit the highest 5.85%; Shenzhen Stock Exchange 1 day R- 001 the highest interest rate touched 7.925%.

(2) China Insurance Regulatory Commission requires China Life Insurance to increase its equity investment. In view of the solvency margin of -115.95% and 74.62% at the end of the third quarter of 2015 and the end of the fourth quarter of 2012, the solvency margin is -2.349 billion yuan and - 282 million yuan, China Life Insurance is a solvency company, the CIRC ordered the company from now on not to increase in stock investment, and take effective response and control measures to effectively guard against investment risks.

(3) In January, public offering of fund sharply shrank one trillion and institutional funds made the market instable to frequently dive. Foreign exchange of financial institutions' fund decreased for about 817.8 billion yuan, the pressure of money out was still large, to suppress the stock rebound.

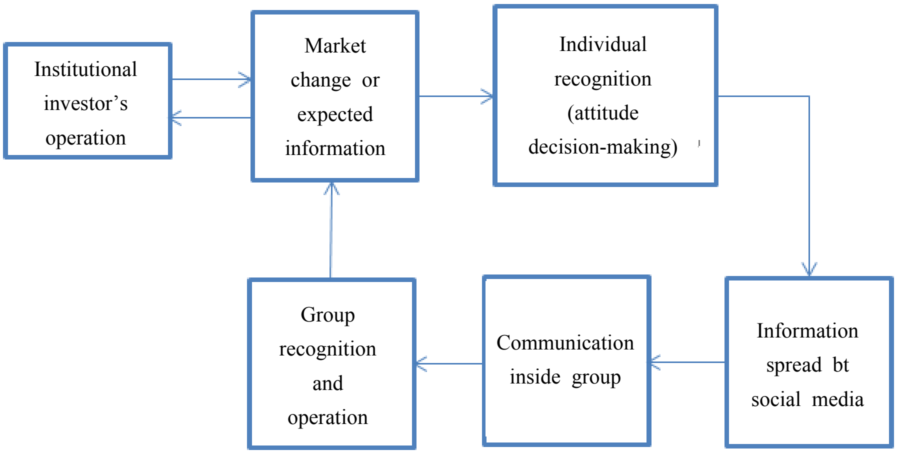
(4) On that day, large-amount trading accounted for a large percentage.

3.6 Model of the mechanism

Through the literature analysis, research interviews and data analysis we get the social media sentiment and the stock trend of the associated mechanism model. On the whole, the basic mechanism is as follows:

There are some changes or expected change information of the market, and social media spread them. After receiving the information from social media, individuals pay attention to some aspects selectively and make their own judgements. In this process, it often relates to rational and emotional recognition, attitudes and decision-making. After that, in the market, group will have its recognition and react to the information. In Chinese stock market, social media emotion has little influence on the stock prices. Chinese stock market is determined by the institutional investors. Social media emotion often follows the trend of stock prices, rather than induces the change of stock prices.

Figure 6. Model of the mechanism



This model can be explained from the following respects:

(1) When the large institutions do not carry out a large number of transactions, social investors contribute to the market trading volume mainly. At this time, the individual investors themselves have their own expectations of the stock prices, through stock forum and other social platform to communicate with each other, forming the mainstream views to guide the investment behavior of social investors. Because the market trading volume is mainly contributed by individual investors, society investors' behavior can have a huge impact on the stock market. At this time, studying the emotional value of social investors can predict the future changes in the stock market.

(2) The operation of a large institution causes information about market changes or expected market changes. The market (expected) change information will affect the individuals' recognitions, and social investors will communicate their emotion through a series of social networking platforms. After that, there will be several consistent viewpoints, which can predict the social investors' investment activities. In this situation, it's the institutional investors who trigger the change of the stock market, affecting the investment activities of social investors. If we just study the influence of social media emotion on the stock prices, it will cause a great error.

4. Summary and discussion

In China, since the institutional investors account for a large part, they have great influence on the stock market, and determine the trend of stock prices. And the retail investors often follow the transactions of the institutional investors. The transactions of institutional investors intrigue change in the stock market, then retail investors catch the information and make their judgements, meanwhile, they may express their opinions in the stock forum, which influence the group recognition. And the group reaction will influence the market in turn, but the influence is quite little since the retail investors are not the dominant in the stock market. So the investor sentiment is not the causality for the change of stock prices, on the contrary, it is the trend of stock prices that induces the change of retail investors' sentiment.

From the above summary, we can also conclude that the higher the participation rate of institutional investors in the stock market, the more rationality of the investors will be raised. Since the institutional investors are the dominant in the market, their transactions will not only affect the stock prices and their own investment income, but also convey the market information, and have influence on the retail investors' sentiment, judgements and actions, thus affecting the stability of the market.

As a result, to promote the healthy development of China's securities market, investor institutionalization is a way to further optimize the direction of China's investor structure. At the same time, in order to enable institutional investors to play a greater role in stabilization, regulatory authority can optimize the institutional structure of investors, and improve the pay evaluation system and the external environment. Besides, regulatory authority should consider reducing the system risk of China's securities market by expanding the size of the securities market and the new investment varieties and improving the quality of listed companies.

In conclusion, there are three main practical implications. First, since the institutional investors have great influence on the stock price in Chinese stock market, China Securities Regulatory Commission should pay more attention to regulate the behavior of institutional investors to normalize the stock market. Second, institutional investors are more rational than individual investors, so the relative authority could consider investor institutionalization as a way to further optimize the direction of China's investor structure. Third, since individual investors' emotion is easily influenced by the information spread by social media and social media plays a more and more important role in stock market, regulatory should establish more regulations to stimulate the healthy and normalized development of social media, so that there will be less fake information on it, individual investors can get more accurate information and make more rational investment decisions.

References

Dai, W., Han, D., Dai, Y. and Xu, D. (2015). Emotion recognition and affective computing on vocal social media. *Information and Management, 52*(7), 777-788.

Frankfurter, G. M. and McGoun, E. G. (2001). Anomalies in finance: what are they and what are they good for?. *International Review of Financial Analysis*, *10*(4), 407-429.

Golder, S. A. and Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and day length across diverse cultures. *Science, 333*(6051), 1878.

Niu, Y., Pan, M. H., Wei, O. and Cai, X. Y. (2014). Emotion analysis of chinese microblogs using lexicon-based approach. *Computer Science.*

Paltoglou, G. and Thelwall, M (2012). Twitter, my space, digg: unsupervised sentiment analysis in social media. *ACM Transactions on Intelligent Systems and Technology*, *3*(4), 1-19.

Prechter, R. R. (1999). *The Wave Principle of Human Social Behavior and the New Science of Socionomics.* New Classics Library, GA.

Quan-Hui, Y. U. and Meng, W. D. (2010). Cointegration analysis on relation of investor sentiment and the composite index of shanghai stock exchange. *Forecasting, 29*(5), 53-57.

Swaminathan, B. (1996). Time-varying expected small firm returns and closed-end fund discounts. *Review of Financial Studies, 9*(3), 845-887.

Wang, M. A. and Sun, J. (2004). Stock market returns, volatility and the role of investor sentiment in China. *Economic Research Journal, 10*, 75-83.

Yang, L., Lin, Y. and Lin, H. (2012). Micro-blog hot events detection based on emotion distribution. *Journal of Chinese Information Processing, 26*(1), 84-83.