ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

The Impact of Bullish Trends in User Online Communities on the Stock Market

Jinhu Li

Guangdong-Hong Kong-Macao Greater Bay Area College of Intelligent Cold-Chain Industries, Guangzhou College of Technology and Business, Foshan 528100, Guangdong, China
l4291027@163.com

Abstract: *In recent years, with the popularization of smart devices and the development of network technology, the proportion of retail investors in my country's stock market is much higher than that of institutional investors. It is becoming more and more important to pay attention to the investment direction and willingness of individual investors . However, as retail investors, most of them do not have professional investment training and guidance, their investment experience is limited, their ability to identify investment information is weak, they are prone to irrational investment behavior, and there are obvious herd mentality and "herd effect". This article mainly adopts the DSSW model and the DHS model to study the situation that most retail investors in the user online community are prone to information evaluation bias when investing, which may lead to the result of investment failure and have a negative impact on rational investors in the stock market. Eventually a chain reaction occurred, stock prices fluctuated violently, and the stock market was turbulent. In addition, this article uses dummy variable regression method and wavelet analysis method, taking Baiyun Airport as an example, selects stocks with a degree of fit greater than 0.650, and conducts secondary screening of data through basic data analysis, and finally conducts multi-factor analysis to obtain the The regression model of the rising phase analyzes that the more the number of bullish trend stock reviews in the online community of users, the more excited investors are to follow the investment, and they are more willing to make large-scale investments, which will play a positive role in promoting the stock market, and the stock price will also Then rose. However, there may also be a crisis that leads to a bubble in the stock market when the forecast is wrong.*

Keywords: *User Online Community, Stock Bullish, Dummy Variable Regression Method, Wavelet Analysis Method, DSSW Model*

1. Introduction

With the vigorous development of the Internet and the landing of 5G technology, a group of new social groups have been born in my country, who have formed an Internet community, that is, an online community for users. The user's online community essentially provides a platform for discussions and exchanges for groups with the same hobbies, including but not limited to investment projects such as stocks and funds. Internet + finance is also gradually growing. The combination of new models has had an impact on the traditional financial industry and has also contributed to a new competitive landscape.

The collision between the Internet and finance is only a matter of time and growth rate. This will inevitably bring new impacts to the traditional financial industry, including the development of new financial products related to the Internet; broaden your business scope; improve your own Service etc. The emergence of the new Internet + finance model is the intersection, interweaving and integration of two industries. It is not a simple business combination, but on the basis of achieving the coverage of mobile network technology and solving information security issues, as the new situation develops A new model is formed naturally, which adapts to the needs of the general environment. The online user community brought by the Internet has a great impact on finance, especially on stocks, no less than the impact and impact of new media reports on stocks, and can even determine the general trend of the stock market to a certain extent.

Butler B S discussed online that community plays an important role in the development of relationships and knowledge transfer within and between organizations. He provides a key potential structural model that is influenced by technological choices and possible causal paths, which has a dynamic impact on the community. Two important community characteristics that may be affected are

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

community size (number of members) and community flexibility (membership who is willing to continue to keep in touch with the community despite the variability and changes in the topics discussed). They used the proposed ASA Online Community Theory (OCASA) to develop a simulation model of community size and resilience. The analysis of the model led to new testable propositions about causal paths. This model affirms some conventional knowledge, but it has counterintuitive meanings [1]. Hau Y S studies the influence of major users on their innovation activities. Through the analysis of the structural equation model of the partial least squares method and the empirical analysis of 140 items of data collected by the online user community, these data are used as an important source of company innovation. Research shows that the main users of users are related to their online user communities. Knowledge sharing related to innovation and users' social capital can fully coordinate this positive relationship. However, there is no empirical research to explore the perceived behavioral control of major users on social capital relationships in online user communities [2]. One of Singh A K's outstanding points is that the development of the stock market has a positive impact on economic growth. The role of the stock market is very important because it leads to the formation of capital in the economy for the production of goods and services, which leads to the growth of the physical sector. However, this is only possible if the stock market is efficient enough to transfer savings from the deficit payer unit to the surplus payer unit. Therefore, his research suggests using a completely modified ordinary least squares model to estimate the determinants of inventory efficiency. The analysis results show that although the risk-free interest rate and market value both have a positive and significant impact on stock returns, the market value has a greater impact. In terms of dynamic analysis, the error correction model shows that the adjustment speed is about 50%, and the time required to rebuild long-term balance is about two years. Since per capita capitalization is one of the important factors that determine the efficiency of the stock market, the government should bring new changes. However, the analysis data is still not accurate enough [3].

The innovations of this article are: (1) Combining stock investment with the investment behavior of investors in behavioral finance, studying the DSSW model and DHS model, and analyzing the information evaluation bias and behavior that individual investors are likely to produce in user online communities Bias, the impact on the stock market; (2) Using dummy variable regression and wavelet analysis, through variance analysis, residual analysis, and regression model analysis, the impact of the number of stock reviews on stock price trends is obtained; (3) The regression model analysis of stock price and five-day moving average and ten-day moving average yielded the best buying price and selling price to buy stocks, which has guiding significance to investors to a certain extent.

2. Impact of Bullish Trends in User Online Communities on the Stock Market

The stock market is fickle and unpredictable. Every user in the online community wants to obtain relevant information through their own channels, grasp the forecast of the stock market's trend, and make the right investment choices. There are many existing technical methods for stock analysis in my country, such as MA moving average, MACD exponential smoothing similarity and difference moving average, EXPMA index average, K-line method, etc. [4]. These most basic methods have a weakness, that is, there are time delays, and they cannot reflect the basic trend of stock changes in a timely manner. Therefore, investors cannot make accurate investment choices. For the analysis of the influence of the bullish trend in the user online community on the stock market, this article uses dummy variable regression and wavelet theory to study, based on statistical data, to grasp the large change trend of the market and individual stocks

2.1 Dummy Variable Regression Method

(1) Calendar effect

The calendar effect mainly refers to the abnormal returns, fluctuations and higher-order matrices generated by dividing holidays, weeks, months, and quarters in the financial market in connection with these cycles [5]. The calendar research method is not very sensitive to the wrong setting of the pricing model and can well control the cross-sectional dependence between samples.

The first step regression analysis model:

$$B_{\mu t} = \alpha_{\mu} B_{mt} + C \tag{1}$$

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

Where $B_{\mu t}$ is the volatility of the stock on day t, and B_{mt} is the volatility of the Shanghai Stock Exchange Index on day t

The second step uses three-factor model analysis: regression analysis model:

$$\alpha_{\mu} = \beta G_{\mu} + \gamma R_{\mu} + \theta V_{\mu} + C \tag{2}$$

α_{μ} Is (1) the regression coefficient of the stock μ volatility to the volatility of the Shanghai Stock Exchange, V_{μ} is the total market value of the stock μ at the end of the year, G_{μ} is the number of stock μ reviews of the stock, and R_{μ} is the year-end return on equity of the stock μ .

The dummy variable regression method is used more in the calendar effect. The data range it uses can be limited by time. More and more scholars also pay attention to the research of its model and theory, and conduct statistical tests [6]. Calendar effects can effectively reflect users online community bullish ups and downs affect the extent and duration of changes in trends and cyclical changes in the stock market. In addition, some studies have found that the calendar effect is more obvious in smaller companies. There are currently few studies linking it to large-scale companies or listed companies, so further research experiments can be carried out in this direction in the future [7-8].

(2) Control variable method.

We use this method to select data results with a fit degree of more than 0.650 in the model of formula (1). Discuss the reasons for the fluctuation of its data, mainly considering the following three aspects: 1) Systematic risk, that is, non-diversified risk; 2) Non-systematic risk, which is risk that can be diversified through investment portfolio; 3) Investor's psychological expected results Relevance to the stock market. In the data screening process, the volatility of individual stocks and the overall volatility of the Shanghai Stock Exchange are matched and compared, and the individual stocks that are mainly affected by the third factor are selected, which is conducive to better analysis of the bullish trend in the online community of users and the volatility of individual stock Impact.

2.2 Wavelet Theory

Wavelet theory is a time-frequency analysis method, which can automatically adjust according to the provided time domain and frequency domain, and achieve an analysis method that meets the needs of reality while being localized [9].It is based on Fourier analysis, and its progress lies in its ability to collect the subtleties of various time periods and frequency bands, and is extremely flexible in application. It is called a time-frequency microscope [10].

(1) The theoretical basis of wavelet transform

The general form of wavelet transform that can be transformed is continuous wavelet transform, which is defined as:

Definition 1 Let the function $\psi(x) \in L^2(R)$ meet the following conditions

$$\int_R \psi(x) dx = 0 \tag{3}$$

$\psi(x)$ is called basic wavelet.

Introduce scale factor (stretch factor) m and translation factor n, m and n satisfy m, n $\in R$ and m $\neq 0$

Expand and translate the basic wavelet, and get the following formula

$$\psi_{m,n}(x) = |m|^{-1/2} \psi_{m,n}\left(\frac{x-n}{m}\right) \tag{4}$$

We call $\psi_{m,n}(x)$ the analysis wavelet that satisfies the expression.

Continuous wavelet transform（CWT）：

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

The continuous $f(x) \in L^2(R)$ wavelet transform (CWT) of the function is defined as

$$CWT_{m,n} = \int_R f(x)\overline{\psi_{m,n}(x)}dx = |a|^{-1/2}\int_R f(x)\overline{\psi_{m,n}\left(\frac{x-n}{m}\right)}dx \tag{5}$$

Where $\overline{\psi_{m,n}(x)}$ is the conjugate function. If it is a real function, then $\overline{\psi_{m,n}(x)} = \psi_{m,n}(x)$.

If the basic wavelet satisfies the following formula, it is called an allowable wavelet.

$$\int_R \frac{|\psi(x)|^2}{|x|}dx \langle \infty \tag{6}$$

Discrete Wavelet Transform (DWT):

Continuous wavelet transform has an important basic role in research. In actual situations, DWT is used more often. The prerequisite for DWT base is to be orthogonal and complete, and then discrete acquisition of scale factor m and translation parameter n[11], get the following formula:

$$m = m_0^a, \quad m_0 \rangle 0, \quad a \in Z$$

$$n = bn_0 m_o^a, \quad n \in R, \quad b \in Z$$

The wavelet transform obtained by formula (5) is

$$\psi_{a,b}(x) = m_0^{-a/2}\psi\left(m_0^a x - bn_0\right) \tag{7}$$

Therefore, the discrete wavelet transform is defined as

$$DWT_{m,n} = \int_R f(x)\psi_{a,b}(x)dx \tag{8}$$

(2) Binary wavelet transform:

Assign and take values based on DWT, and $m_0 = 2$ the result is called dyadic wavelet and dyadic wavelet transform. Adding the assignment $n_0 = 1$ is called the binary orthogonal wavelet transform [12].

Suppose $\psi(x) \in L^2(R)$, if there are constants A and B, such that $0 < A \le B < \infty$

$$A < \Sigma\left|\psi\left(2^k\right)\omega\right| < B \tag{9}$$

$\psi(x)$ is called dyadic wavelet.

Dyadic wavelet is also called admissible wavelet, which is a special case of continuous wavelet transform after the scale factor m is discretized.

The physical meaning of the dyadic discretization of the scale factor m is to divide the two-octave frequency in the frequency domain [13-14].

(3) Multi-resolution analysis

There are two parts in any actual signal $f(x)$, namely the high frequency and the low frequency part. By expanding the low frequency part, we introduce a scale function. In the multi-resolution analysis, the scaling function is to expand the low-frequency part of $f(x)$, and use the wavelet function to analyze the high-frequency part [15]. This is also of great significance for wavelet transform.

It can be seen from Figure 1 that this analysis method does not decompose the high-frequency part, but performs multiple expansions and disassembly analysis on the low-frequency part to achieve more accurate resolution standards and requirements.

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

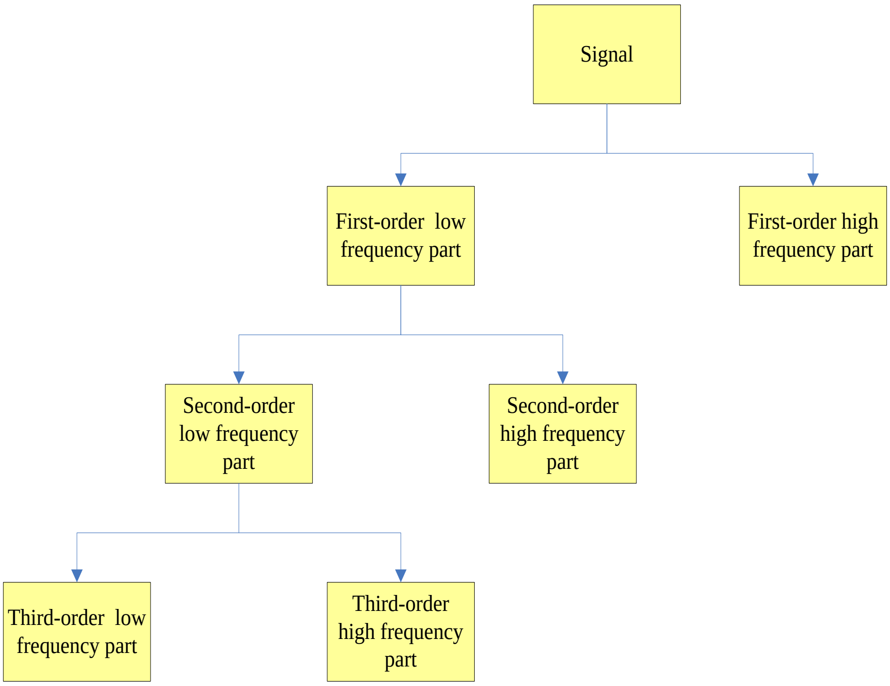

Figure. 1 Multi-resolution analysis structure hierarchy diagram

3. Experiment on the Influence of Bullish Trends in User Online Communities on the Stock Market

3.1 DSSW Model

The DSSW model is a noise trading theoretical model proposed by Delong et al. This model can be used to illustrate that in the environment of user online communities, the form of concentrated discussion and exchange of information affects investors' emotions and judgments, and ultimately affects investors' investment behavior , Make right or wrong investment predictions, which leads to fluctuations in stock prices and the entire market [16-17].

The DSSW model assumes that the entire market environment contains two alternative investment projects: one is a completely safe asset A, which can be regarded as a short-term risk-free bond, which can continuously bring stable returns q, and there is no purchase quantity The other is the risky asset B, which will fluctuate in price with the market trend, but it can also provide fixed income q, and the quantity is fixed. In different situations, the influence of noise investors is added, so risk asset B The price of is unstable and will change with market changes, which is defined as p_t

The model only includes two types of investment entities, namely, rational investors a and noise traders b (noise traders are groups that are susceptible to misjudgments by users' online communities). Among them, let noise traders be μ , rational investors The number of investors is $1-\mu$.

Both types of investment entities can, in accordance with the principle of maximizing their own interests, measure the risk tolerance range and expected return range, and select a portfolio of assets that suits them. Under normal circumstances, rational investors have a correct assessment of themselves and the market, and can make correct investment decisions. However, due to the presence of noisy traders, such entities will make false predictions based on investment information, that is, there is an estimation error, which generates investor sentiment σ_p .The point of this model is that the variance of asset prices p_t is strongly correlated with the false estimates of noise traders.

$$\sigma^2_{t,p_{t+1}} = \sigma^2_{p_{t+1}} = \frac{u^2\sigma^2_\rho}{(1+r)^2} \tag{10}$$

It can be seen from formula (4) that changes in investor sentiment greatly affect stock prices. For

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

example, the government has introduced relevant favorable policies. In this case, investor sentiment in the online community of users will rise. The bullish trend has formed the "herding effect" in the financial anomaly, and noisy investors are very likely to push the market toward a bubble, which intensifies the volatility of my country's stock market.

The model believes that if noise investors' sentiment deviations are corrected in time, the stock price will self-adjust in a short period of time and return to the original stable level; however, if noise investors continue to have such deviations, it will not only be rational Investors have a serious impact, and will produce drastic fluctuations in the stock market [18]. In the latter case, the volatility formula of asset prices proposed by DSSW is:

$$\sigma_p^2 = \frac{u^2\sigma_\rho^2}{\left[r+(1-\phi)\right]^2} = \frac{u^2\sigma_\eta^2}{\left[r+(1-\phi)\right]^2\left(1-\phi^2\right)} \tag{11}$$

Among them, the automatic regression coefficient ϕ, η is disturbance.

At present, the proportion of retail investors in my country's stock market is significantly higher than that of professional institutional investors such as various investment funds, bonds, insurance, stocks, etc. Compared with institutional investors, individual investors are more vulnerable due to lack of investment experience. The influence of "herding effect", especially in user online communities, is more likely to produce irrational investment behavior. Retail investors tend to listen to gossip, and often do not pay attention to official announcements, company operating conditions, financial statements, etc. Conduct rational thinking, produce investment bias, and have a bad impact on the stock market.

3.2 DHS Model

The DHS model studies the extent to which investors reflect on information and how much influence the market will have. It is a related research based on behavioral finance, especially for the short-term dynamics and long-term reversal of stock prices. It emphasizes investors It is easy to produce the illusion of overconfidence and bias in self-attribution [19].

It is assumed that investors have two kinds of biases when making investment decisions. One is overconfidence, and the other is biased self-evaluation or attribution bias [20]. They will also habitually overestimate their own predictive ability, affirm their prediction results, and treat their prediction errors irrationally. Overconfident investors will be more willing to trust private information, follow the direction of investment decisions, and refrain from rational thinking and research, leading to overreacting investments. When the correct public information arrives, the overreaction price will be reversed [21].

Another type of bias in the DHS model is attribution bias, which refers to the deviation of the investor's reflection results after the investment behavior. For successful investment projects, investors often think that it is the result of their own high ability; When there is a situation of investment failure, they tend to think that it is an uncontrollable factor caused by external noise, which has little to do with their own ability [19]. All of this stems from the deviation of their attributions, the inability to treat the occurrence of an event rationally and objectively, and they often choose to doubt or abandon their unfavorable news and ignore them. In general, attribution bias not only leads to short-term inertial behavior and long-term reversal, but also encourages overconfidence [22].

(1) Expected price route without overconfidence

Figure 2 describes all the contents of the DHS model well. The thick solid line represents the expected price, and the thin solid line represents a completely rational price level. The process change of the line chart is described as follows: At t1, the investor heard a noisy private message, and due to his overconfidence, he made an overreaction, that is, when the stock price is too high (the stock price is higher than the reasonable price space) In the case of still buying the stock. At t2, a noisy public signal appeared in the market, and the excessively high price was partially corrected, that is, the price level was reduced. At t3, noisy public information appears again, and the accuracy of the information is further improved. At t4, the market officially announced relevant information, with the best information accuracy, and the price was completely corrected, that is, the price returned to a normal level. The part before t1 is called the "over-reaction stage", and the parts after it are called the "correction stage".

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

At present, there is a relatively common view that they believe that positive return auto correlation is mostly caused by insufficient response to new information, and negative return auto correlation can only occur when overreacting to new information [23]. But the DHS model points to a different point of view. DHS believes that positive return auto correlation may also be caused by continuous overreaction to new information, followed by long-term price correction. On the whole, the short-term positive auto correlation is consistent with the long-term negative auto correlation.

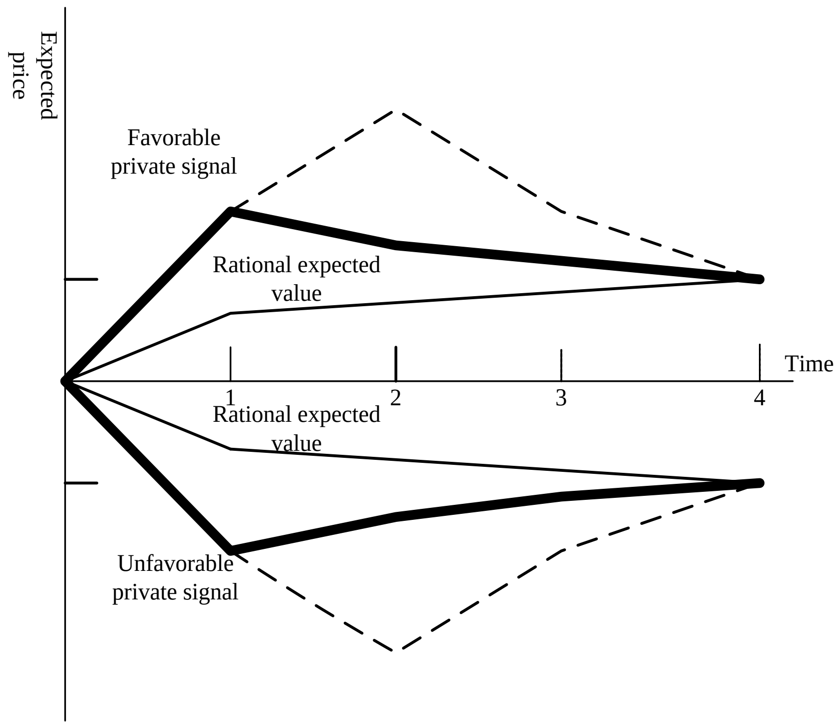

Figure. 2 Price function determined by overconfident investors

Experts put this model together with the results of many events and found that the abnormal price trend after a certain event and the initial price performance of the event were caused by the same signal. This is generally considered to be the market's insufficient response to the event. Performance [24]. However, the explanation of the DHS model is that the market's insufficient response to the event is not a reason that can be fully explained. There is only one case in which insufficient response can produce predictability. That is, when the market has mispricing, the event will Targeted measures.

(2) The expected price route when confidence depends on the behavior result

The following description is the behavioral results in the case of overconfidence. Some psychological research results show that the results of people's behaviors greatly affect people's self-confidence [25]. In the dotted line in Figure 2, what is being explored is the result of biased self-attribution behavior, where the 0-1 part of the dotted line coincides with the thick solid line in the figure. The difference from the above is that under the effect of biased self-attribution, at time t2, noisy public information continues to increase investors' enthusiasm for investment and further aggravates overreaction. Therefore, at time t2, it is not the same as before. The stock price has been corrected, but it deviates more from the average price. It is not until the official information is released that the stock price can be adjusted to a normal level.

4. Impact of Bullish Trends in User Online Communities on the Stock Market

4.1 Dummy Regression Variables

(1) Basic data analysis

This article selects the Baiyun Airport Stock (600004) as an example, the data date is from January 5, 2018 to January 4, 2019, and the volatility of the whole year is analyzed by regression model. The analysis results are as follows:

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

From Table 1, it can be calculated that the regression model for the whole year of Baiyun Airport in 2018 is: $B_{it} = 1.640 B_{mt} - 0.005$, among them, $\alpha = 1.640$,the fitted value is 0.856, and the volatility of the above securities is referenced, and the fluctuation of individual stocks is analyzed.

Then, divided into rising and falling stages, the regression analysis model results are as follows:

The regression model for the rising phase is: $B_{it} = 1.442 B_{mt} - 0.001$

The regression model for the rising phase is: $B_{it} = 1.729 B_{mt} - 0.008$

Table. 1 Regression analysis results for the whole year

Stage	Data variable	Number of samples	average value	Max	Minimum	median
annual	Correlation coefficient α_i	166	1.358	1.875	0.139	1.399
	Goodness of fit	166	0.633	0.892	0.006	0.781

(2) Secondary screening

In accordance with the requirements of the controlled variable method, we calculated its goodness of fit, and selected 110 data with a fit value of more than 0.650 for concentrated discussion. The result is that the stock year stage, the rising stage, and the falling stage have a large correlation with the volatility of the Shanghai Stock Exchange. Model, that is, to study data fluctuations that are mainly affected by systemic risks.

Table. 2 Descriptive statistics of secondary screening data variables

stage	type of data	Number of samples	Average value	Maximum value	Minimum value	Median
annual	Correlation coefficient α_i	110	1.375	1.973	0.454	1.453
	Goodness of fit	110	0.725	0.780	0.632	0.758
	Number of stock reviews	110	147	386	2	125
	Market value of individual stocks at the end of the year	110	450Billion	5859Billion	18Billion	197Billion
	Year-end return on net assets of individual stocks	110	5.83%	27.14%	-4.58%	5.63%
Rising phase	Correlation coefficient α	110	0.896	1.856	0.003	0.851
	Number of stock reviews	110	70	198	0	68
Down phase	Correlation coefficient α	110	1.368	1.954	0.589	1.378
	Number of stock reviews	110	77	275	0	65

It can be seen from Table 2 that the greater the number of individual stock reviews (that is, the number of user's online community forecasting comments on the stock trend), the less volatility is affected by the SSE market, and the higher the degree of inhibition in the rising market. Table 2 reflects that the higher the return on net assets of individual stocks, the less affected the volatility, that is, the two show a negative correlation.

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

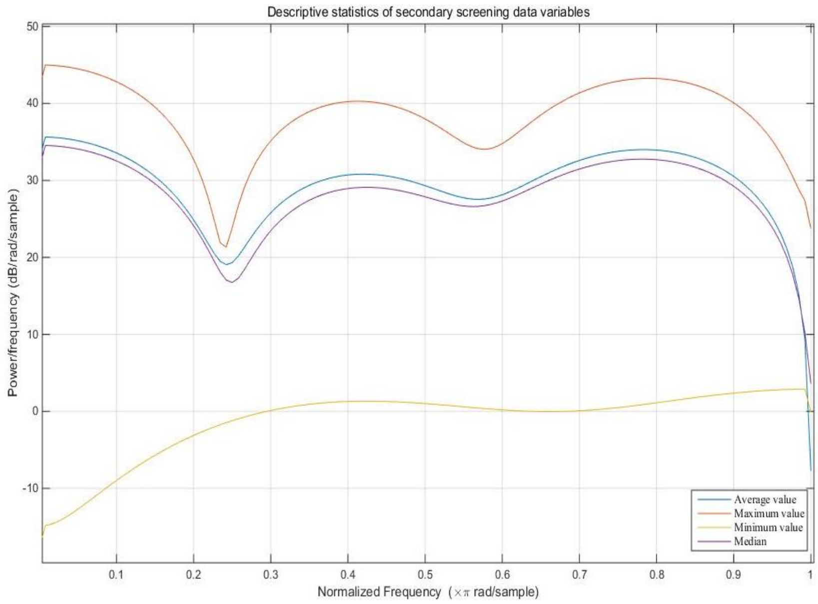

Figure 3 Descriptive statistics of secondary screening data variables

It can be seen from Figure 3 that the coefficient value α in the rising phase of individual stocks is smaller than that in the falling phase, which also shows that the volatility of individual stocks in the rising market is less affected by the overall volatility of the market.

(3) Conduct a three-factor model analysis

$$\alpha_i = \beta G_i + \gamma R_i + \theta V_i + C \tag{12}$$

Among them, α_i is the correlation coefficient of the volatility of the Shanghai Stock Exchange to the volatility model of stock i in formula (1), G_i is the number of stock comments for stock i, R_i is the year-end return on net assets of stock i, and V_i is the year-end circulating market value of stock i. The analysis results of the three-factor model in the rising phase are shown in Table 3.

Whole year period: $\alpha_i = -0.0007G_i - 0.0158R_i - 0.0001V_i + 1.6250$

Decline stage: $\alpha_i = -0.0014G_i - 0.0115R_i - 0.0001V_i + 1.5688$

Rising phase: $\alpha_i = -0.0025G_i - 0.0176R_i + 0.0002V_i + 0.8965$

Table. 3 Three-factor model analysis results of the whole year, rising stage, and falling stage

Stage	Variable	Value	t-Statistics	prob	goodness of fit R-squared
Whole year period	constant	1.6250	40.0506	0.0000	0.3925
	β	-0.0007	-3.0358	0.003	
	γ	-0.0158	-2.9635	0.0039	
	θ	-0.0001	-4.3845	0.0000	
Down phase	constant	1.5688	34.1295	0.0000	0.2582
	β	-0.0014	-2.6962	0.0084	
	γ	-0.0115	-1.7589	0.0786	
	θ	-0.0001	-2.1569	0.0303	
Rising phase	constant	0.8965	12.9586	0.0000	0.1635
	β	-0.0025	-2.5653	0.0218	
	γ	-0.0176	-1.9565	0.0563	
	θ	0.0002	-3.5026	0.0018	

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

From the data in Table 3, it can be concluded that the number of individual stock reviews has a negative correlation α with the volatility rate of the Shanghai Stock Exchange and individual stocks. The more the number of stock reviews, the lower the correlation α and the smaller the value. In the rising stock market, the number of stock reviews further restrained the value α , $|\beta|$ rising> $|\beta|$ falling.

In general, in the stock market, the number of stock reviews of individual stocks increases, and its return on equity is high, so the stock price fluctuates very little with the market; in addition, in the rising market, the degree of inhibition is greater than that in the falling market The degree is higher and the effect is more obvious. Therefore, an appropriate increase in the number of stock reviews and concentrated discussions in user online communities are conducive to information exchange to a certain extent, can curb the problem of excessive stock price fluctuations, and can also achieve strong risk management and control.

4.2 Wavelet analysis

Figure 4 selects the daily closing price data of AVIC Sanxin for the whole year. The time period is from January 5, 2018 to January 4, 2019.

Combine the original data chart of AVIC Sanxin (as shown in Figure 4) with the 5-day moving average and the 10-day moving average to obtain a wavelet analysis chart (as shown in Figure 5). The wavelet analysis graph first uses discrete wavelet transform on the original data graph, and extracts the low-frequency sub-signals instead of moving average. The low frequency signal is extracted because it can fully reflect the basic trend and direction of the stock price, and the information is synchronized and timely. Then, use Sym6 wavelet to extract the low-frequency part of the horizontal discrete wavelet transform to replace the 10-day moving average, and use the same method to replace the 5-day moving average with Sym4 wavelet, and finally get the wavelet analysis chart. It can be seen from the wavelet analysis graph that the buy signal in the graph is the golden intersection, and the sell signal is the death intersection.

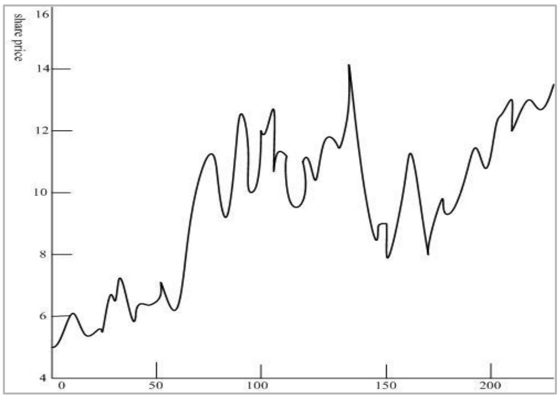

Figure. 4 The raw data of the closing price of AVIC San xin 2018-1-5~2019-1-4

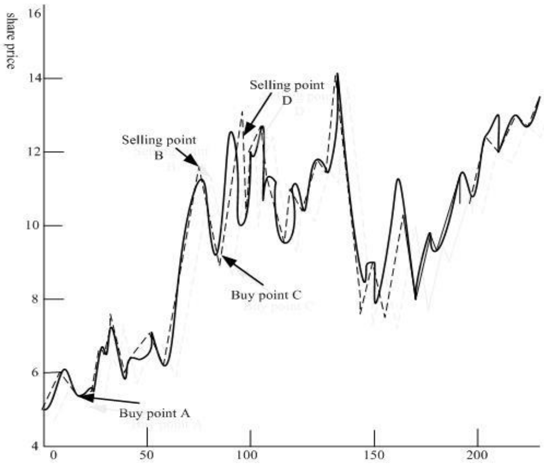

Figure. 5 Wavelet analysis graph

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

It can be seen from Figure 5 that comparing the intersection of the moving averages, replacing the intersections of the 5-day and 10-day moving averages with low-frequency information is significantly earlier. The specific data is shown in Figure 6.

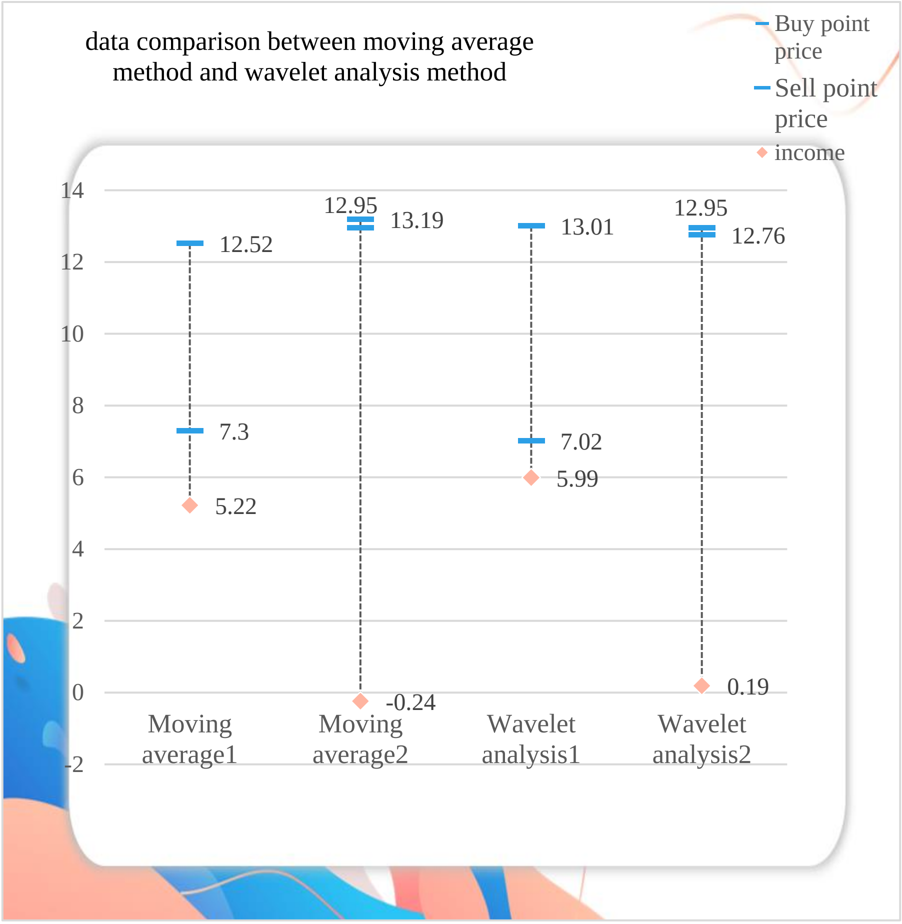

Figure. 6 Data comparison between moving average method and wavelet analysis method

It can be seen from Figure 6 that the wavelet analysis method accurately depicts the trend of stock prices, and can accurately specify the timing of buying and selling according to the intersection point, bringing good returns to investors. So for users in an online community bullish trend, investors need to control the trend of wavelet analysis, will be able to determine the general trend toward the right and wrong, to make the right investment choices. At the same time, we must also know clearly that the disadvantage of wavelet analysis is that it is still a difficult point for ordinary investors to choose between wavelet and wavelet base.

4.3 Regression Model Analysis of Stock Price and 5-Day Moving Average and 10-Day Moving Average

Suppose that the closing price of the stock on the day is y , the average price of the day on the five days is x_1, the average price of the ten days is x_2 , and the closing price is a function of the average price of the five days and ten days $y = ax_1 + bx_2 + c$. The following data table can be obtained after the wavelet analysis method adopts the denoising processing.

Table. 4 Regression statistics

Regression statistics	
Multiple R	0.999422
R Square	0.998856
Adjusted R Square	0.887609
Standard error	0.285325
Observations	11

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

It can be seen from Table 4 that the standard error of the regression model is 0.285325, and the R Square value is about 0.99, which shows that the 99% probability of stock price changes can be solved by the linear regression equations of mac5 and mac10 (mac5 is the 5-day moving average, mac10 is the 10-day moving average).

Table 5. Analysis of Variance

	df	SS	MS	F	Significance F
Regression analysis	2	634.3355	317.1686	3896.335	1.10632E-12
Residual	9	0.732625	0.081405		
Total	11	635.0892			

Table. 6 Regression coefficients

	Coeficients	Standard error	T Stat	P-value	Lower limit 95.0%	Upper limit 95.0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A
X1	0.8874	0.3739	2.3740	0.0416	0.0418	1.7330
X2	0.1175	0.3718	0.3159	0.7596	-0.7236	0.9584

The results of the analysis of variance in Table 5 can be used to test the hypothesis that all the regression coefficients in Table 6 are 0. The output result is P and the output letter is marked as "Significance F". From the data in Table 5, P=1.10632E-12 can be obtained, which can explain the probability of the relationship between the stock price and various variables in the overall random sample, thereby drawing the conclusion that at least one significant relationship exists.

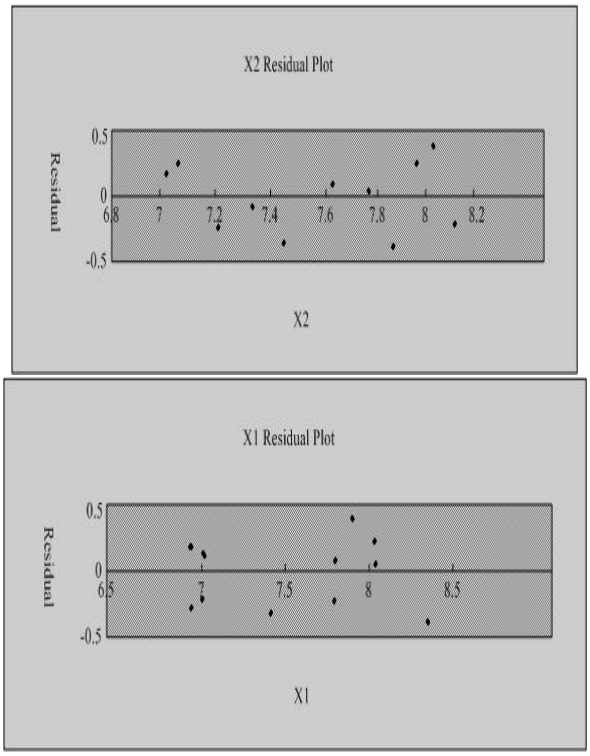

Figure. 7 Residual error analysis

The residual analysis chart in Figure 7 shows that the data is basically randomly distributed, which shows that after comprehensive consideration, the relationship between "stock price" and "mac5" can be regarded as linearly related.

Through the comprehensive calculation of the above several charts, this regression equation can be obtained: $y = 0.887399x_1 + 0.117409x_2$.The significance of establishing this regression equation lies in the conclusion that the relationship between the stock price and various factors in the market can be analyzed. Obviously, the bullish trend in the online community of users has a great relevance to the stock market. Given a certain scale, it can have a positive or negative impact on the stock market.

Of course, the stock market is unpredictable, and stock prices fluctuate under the combined effect of many factors. Investors should rationally view the forecast results on the market and invest rationally.

5.Conclusions

This article mainly studies the impact analysis of the bullish trend in users' online communities on the stock market, using a combination of qualitative and quantitative research methods. The main innovation of this paper is the ingenious combination of investment behavior and investment psychology, the construction of DSSW model and DHS model, and analysis of investors in user online communities that are prone to information biases in predicting stock trends, and this overconfidence and Attribution bias will lead to the failure of investment results and cause violent fluctuations in the stock market.

This article uses dummy variable regression method and wavelet analysis method, through variance analysis, residual analysis, and regression model analysis to get the influence of the number of stock reviews on stock price trends. And analyzed the regression model of stock price and five-day moving average and ten-day moving average, and got the best buying point and selling point to buy stocks, which has guiding significance to investors to a certain extent.

The disadvantage of this article is that the wavelet analysis method does not comprehensively consider the actual situation of most investors, it is difficult to select the appropriate value of wavelet and wavelet base, and it fails to make appropriate investment decisions for investors. In addition, the stock market is ever-changing, failing to comprehensively and comprehensively consider the impact of various factors on the stock market, and the scope of research is limited. In the process of stock investment, investors should comprehensively consider the impact of various factors, study relevant data, and finally make a favorable investment decision that suits them.

References

[1] Butler B S , Bateman P J , Gray P H , et al. An Attraction-Selection-Attrition Theory of Online Community Size and Resilience[J]. Mis Quarterly, 2018, 38(3):699-728.
[2] Hau Y S , Kang M . Extending lead user theory to users' innovation-related knowledge sharing in the online user community: The mediating roles of social capital and perceived behavioral control[J]. International Journal of Information Management, 2016, 36(4):520-530.
[3] Singh A K , Nainwal N . Estimating the Long-Run Determinant of the Efficiency of the Stock Market in India[J]. Asia-Pacific Journal of Management Research and Innovation, 2017, 13(1-2):70-80.
[4] Reboredo J C , Ugolini A . Quantile dependence of oil price movements and stock returns[J]. Energy Economics, 2016, 54(Feb.):33-49.
[5] Yang C , Gao B , Yang J . Option pricing model with sentiment[J]. Review of Derivatives Research, 2016, 19(2):147-164.
[6] Miwa K . Investor sentiment, stock mispricing, and long-term growth expectations[J]. Research in International Business & Finance, 2016, 36(jan.):414-423.
[7] Loney N . STOCK PRICE ANALYSIS[J]. Windpower monthly, 2016, 32(4):48-49.
[8] Aydo An B , Tun G , Yelkenci T . The impact of oil price volatility on net-oil exporter and importer countries' stock markets[J]. Eurasian Economic Review, 2017, 7(2):1-23.
[9] Tsukioka Y , Yanagi J , Takada T . Investor sentiment extracted from internet stock message boards and IPO puzzles[J]. International Review of Economics & Finance, 2018, 56(JUL.):205-217.
[10] Xiao J , Hu C , Ouyang G , et al. Impacts of oil implied volatility shocks on stock implied volatility in China: Empirical evidence from a quantile regression approach[J]. Energy Economics, 2019, 80(MAY):297-309.
[11] Rehman M U , Apergis N . Do global sentiment shocks spillover towards emerging and frontier markets?[J]. Journal of Economic Studies, 2020, 47(3):433-465.
[12] Amrani N , Joan Serra-Sagristà, Laparra V , et al. Regression Wavelet Analysis for Lossless Coding of Remote-Sensing Data[J]. IEEE Transactions on Geoence & Remote Sensing, 2016, 54(9):5616-5627.
[13] Yang J J , He Z B , Zhao W J , et al. Assessing artificial neural networks coupled with wavelet analysis for multi-layer soil moisture dynamics prediction[J]. ences in Cold and Arid Regions, 2016, 8(002):116-124.
[14] Bousefsaf F , Maaoui C , Pruski A . Peripheral vasomotor activity assessment using a continuous wavelet analysis on webcam photoplethysmographic signals[J]. Bio-medical materials and engineering,

ISSN 2706-6827 Vol. 3, Issue 7: 1-14, DOI: 10.25236/IJFS.2021.030701

2016, 27(5):527-538.

[15] Alcala C M , Kelley M C , Ulwick J C . Nonturbulent layers in polar summer mesosphere: 1. Detection of sharp gradients using wavelet analysis[J]. Radio ence, 2016, 36(5):875-890.

[16] Mizeva I , Dremin V , Potapova E V , et al. Wavelet Analysis of the Temporal Dynamics of the Laser Speckle Contrast in Human Skin[J]. IEEE Transactions on Biomedical Engineering, 2019, 67(7):1882-1889.

[17] Kumar A , Reddy M . Multi resolution wavelet analysis for damage detection using strain energy variation in structure[J]. International Journal of Pure and Applied Mathematics, 2019, 118(18):4435-4448.

[18] Babichev S , Mikhalyov O . A Hybrid Model of 1-D Signal Adaptive Filter Based on the Complex Use of Huang Transform and Wavelet Analysis[J]. International Journal of Intelligent Systems and Applications, 2019, 11(2):1-8.

[19] Muanenda S . the impact of health-related problem on academic achievement of students: application of dummy variable regression model[J]. International Journal of Advanced Research, 2018, 6(9):350-357.

[20] Bell A , Holman D , Jones K . Using Shrinkage in Multilevel Models to Understand Intersectionality[J]. Methodology, 2019, 15(2):88-96.

[21] Fekri, Ali, Shawtari, et al. Efficiency and bank margins: a comparative analysis of Islamic and conventional banks in Yemen[J]. Journal of Islamic Accounting and Business Research, 2019, 10(1):50-72.

[22] Seung-Hoon E , Hu-Rak P , Jakyeom S , et al. Multiple Regression Analysis to Estimate the Unit Price of Hanwoo (Bos taurus coreanae) Beef[J]. Korean Journal for Food ence of Animal Resources, 2017, 37(5):663-669.

[23] Seung-Hoon E , Hu-Rak P , Jakyeom S , et al. Multiple Regression Analysis to Estimate the Unit Price of Hanwoo (Bos taurus coreanae) Beef[J]. Korean Journal for Food ence of Animal Resources, 2017, 37(5):663-669.

[24] Jaisinghani D , Kaur M , Inamdar M M , et al. Analyzing seasonal anomalies for Israel: evidence from pre- and post-global financial crisis[J]. Managerial Finance, 2019, 46(3):435-450.

[25] Chen R , Ghoul S E , Guedhami O , et al. Do state and foreign ownership affect investment efficiency? Evidence from privatizations[J]. Journal of Corporate Finance, 2017, 42:408-421.