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Understanding the role of social media sentiment in identifying irrational herding behavior in the stock market

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ABSTRACT

This study examined the role of social media sentiment in identifying irrational herding behavior in the stock market. We selected the Chinese stock market, where majority are retail investors, as the object of analysis, and analyzed the sentiment of 227,353 microblog text messages through deep learning techniques and constructed the identification method of herd behavior. Results show that social media sentiment has a significant impact on irrational herding behavior in the stock market. The findings of the study complement the theory of investor behavior and can aid in investors' trading decisions and financial regulators' policy recommendations.

1. Introduction

The role of irrational behavior in the operation of capital markets has been widely studied since Keynes (1937) referred to "animal spirits" in explaining abnormal fluctuations in economic activity. As early as 1990, Long, Shleifer, and Waldmann (1990) also confirmed that noise traders' trading behavior is more likely based on emotions rather than rational analysis. Based on this, we try to give a human dimension to the stock market by exploring herd behavior, a type of investment behavior that imitates others and disregards one's own viewpoint. This phenomenon is closely related to human psychology and sociology. Ftiti, Fatnassi, and Tiwari (2016) mentioned that noise traders bring about highly synergistic movements in the oil and gold markets during crises. In addition, the tulip fever of the 17th century, the Internet bubble of 1995–2000, and the Chinese stock market crash of 2015 are all examples of greed and strong herd behavior driving the market. As one of the best-known financial anomalies, herding is widely believed to lead to excessive volatility, price fluctuations, and illiquidity (Bikhchandani & Sharma, 2001; Shiller, 2003).

To detect the herding effect, the conventional approach is to determine herding that is implied in asset prices (Chang, Cheng, & Khorana, 2000; T. C. Huang, Wu, & Lin, 2016). However, as herding is highly linked with human beings' mental and social activities, this measurement may be delayed since stock market data are consequences of investor decision-making behavior (Raffaele et al., 2017). Prior studies have shown that investor sentiment significantly predicts stock returns (D. S. Huang, Jiang, Tu, & Zhou, 2015; Liang, Tang, Li, & Wei, 2020) and can characterize the price dynamics of stocks (Jawadi, Namouri, & Ftiti, 2018), and this effect varies by market condition with a certain threshold level (Namouri, Jawadi, Ftiti, & Hachicha, 2018). Given the significant role of investor sentiment in stock returns, instead of the conventional path (cross-sectional dispersion in stock returns), Ren and Wu (2020) proposed an innovative framework for detecting herding behavior using an investor sentiment index to directly explore herding. They argue that when herding behavior emerges, sentiment about individual stock tends to follow market sentiment, i.e., investors have similar and

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less divergent opinions; thus the deviation of individual stock sentiment from market sentiment can be used to capture the herding effect.

The development of social media in recent years has gradually become an important source of information for investors (Chiou, Knewtson, & Nofsinger, 2019). Many scholars consider social media sentiment as investor sentiment and directly use social media information as a data source to compile and construct an investor sentiment index (Gu & Kurov, 2020; Sul, Dennis, & Yuan, 2017). However, social media sentiment cannot directly represent stockholder sentiment since not all social media users are stock market participants. Hence, we need to make a clear delineation between social media sentiment and investor sentiment to further explore how social media sentiment is transmitted to investor behavior.

We propose the motive of this research, as shown in Fig. 1. We use the absolute value deviation of investor sentiment in the herd effect detection model as a measurement basis, and try to explore the impact of social media sentiment on investor sentiment. Thereafter, we explore the role of social media sentiment in identifying irrational herd behavior in the stock market.

We divide our study into two parts. First, we build a mathematical model to discern herd behavior based on the works Chang et al. (2000) and Hwang and Salmon (2004). Following Ren and Wu (2020), we construct a cross-sectional absolute deviation of sentiment (CADS) based on investor sentiment data from a stock bar forum to examine herd behavior in the stock market by analyzing the convergence of individual stock sentiment and market sentiment, and identifying rational herd behavior driven by fundamental asset value changes, thereby achieving a distinction between rational and irrational herding behavior. Second, we conduct social media sentiment analysis on firm-specific information which, based on natural language processing and deep learning methods, classify the sentiment of social media user-generated content by support vector machine (SVM), long short-term memory neural network (LSTM), and BERT algorithm, and then construct a social media sentiment index. In summary, we try to address the following issues: (1) whether social media sentiment influence investors' herding behavior, and if it can, whether this herding behavior is rational or irrational; and (2) whether the content of the different channel and social attributes of social media posting accounts, such as the official nature of the posting account and the number of followers, will have a differential moderating effect on the impact of herding behavior.

It is found that the impact of social media sentiment in firm-specific information on stock market investor sentiment is significant and exacerbates irrational stock market herding behavior; furthermore, the authority and influence of social media accounts can have a differential impact on irrational herding behavior. Our empirical results show that official social media accounts are more neutral and less likely to influence irrational herding behavior, while unofficial social media accounts' posts reduce the limited rationality of investors. The more followers unofficial social media accounts have, the more likely they are to influence irrational herding behavior. However, this "follower effect" has a certain threshold value, and when the threshold value is exceeded, despite gaining more followers, unofficial social media accounts' posting sentiment no longer influence irrational herding behavior. The advantages of this study are mainly manifested for investors to understand the bias of social media information on their own decision-making behavior and choosing postings with a high degree of credibility in the information selection process can avoid the behavior of blindly following the trend in the face of market hotspots.

The remainder of the paper is structured as follows: Chapter 2 presents a review of related studies and the research hypotheses. Chapter 3 introduces the methods and models used in the study, including sample selection and data collection, indicator calculation, and the herding behavior detection model. Chapter 4 shows the empirical results and analysis. Chapter 5 discusses the relevant research findings. Finally, our study conclusions are drawn in Chapter 6.

2. Literature review and hypotheses development

This section reviews studies on stock market herding behavior and its detection methods, social media sentiment, and investor behavior. Based on the relevant theoretical background, we propose three hypotheses for this study.

2.1. Herding behavior in stock market

Juan, Kolm, Devenow, and Welch (1998) first pointed out that herd behavior should be divided into rational and irrational herd behavior. Rational herd behavior is when rational investors with similar stock preferences react identically to similar information about firm characteristics and fundamentals, and is a behavior based on an integrated analysis of information. For example, when market interest rates fall, stocks become a better investment and investors will try to buy more stocks, which is a rational herd

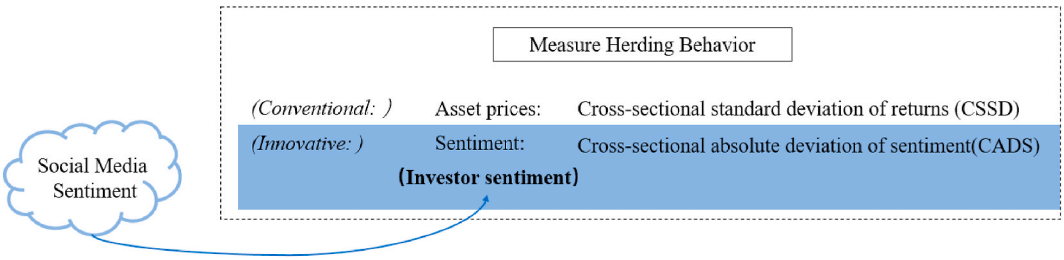

Fig. 1. Research motivation.

behavior. Irrational herd behavior, on the other hand, refers to the behavior of investors with inadequate information and risk assessment, who ignore their a priori information and blindly follow other investors. For instance, when there is a sharp fluctuation in the stock market, some investors will buy and sell a large number of stocks, and driven by herd mentality, other investors will also follow without thinking in order to make a similar investment behavior. These two types of herd behavior can have very different effects on the stock market. Irrational herding behavior can reduce the transparency of information in the capital market, seriously impair pricing efficiency and prediction accuracy, and increase the fragility of the financial system, which is not conducive to the stable operation of the market. On the other hand, rational herding behavior will accelerate the transmission of market information, increase the speed of information absorption by stock prices, and thereby improve market efficiency. Therefore, it is necessary to distinguish between these two types of herding behavior (Chang et al., 2000).

Lin, Tsai, and Lung (2013) studied the relationship between the herding behavior of various investment groups and Taiwan stock market noise, and showed that there is rational herding behavior among institutional investors and irrational herding behavior among retail investors. The buying and selling herding behavior of institutional investors has a predictive power for the increase or decrease of stock prices, but the buying and selling herding behavior of retail investors shows a negative relationship with future stock returns. Alhaj-Yaseen and Yau (2018) used two methods, cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD), to detect the herding behavior of 87 listed companies in the Chinese A-share and B-share markets from 1996 to 2012. The empirical results showed that although herding behavior exists in both markets, the herding effect is weaker in the B-share market than in the A-share market, where investors in the A-share market exhibit rational herding behavior, while investors in the B-share market exhibit rational herding behavior before market liberalization and both rational and irrational herding behavior after this period.

Information scarcity is a norm in the securities market, and incomplete information is a key cause of irrational herd behavior (Chiang & Zheng, 2010). Effective information is not publicly available and confirmed in the market in a timely manner, and there is a corresponding time and economic cost to obtain effective information. Therefore, under the situation of ambiguous and incomplete information, most investors in the market, especially those who are not professional enough, are prone to rely on others' judgment and to practicing blind herd behavior when making decisions.

2.2. Social media sentiment and investor sentiment

Investors have relied on the media for stock-related value information and outlook judgments for many years. Tetlock (2007) first studied the impact of the emotional tone of media coverage on the stock market, and he found that negative financial news increases the risk of stock price declines. Bartov, Faurel, and Mohanram (2018) showed that at least 34%–70% of percent of investors use social media content to some extent to make investment decisions, and their findings underscore the importance of considering the views of tweets when evaluating stock futures, where the value of group wisdom and the diversity and independence of information on social platforms outweighs concerns about the lack of credibility of information, and information from social media is more likely to help investors make decisions than to mislead them. Broadstock and Zhang (2019) tested whether sentiment extracted from Twitter has price predictive power for the stock market. By using the returns of high-frequency traded stocks during the trading day of US public companies as sample data, they show that prices are susceptible to social media coverage of companies and coverage of market conditions. Gu and Kurov (2020) attempted to investigate the informational role of social media and why they are an integral part of investors' strategies. Their study showed that Twitter sentiment provides analysts with information about price targets and quarterly earnings, and that this information accounts for about one-third of Twitter sentiment having predictive power for stock returns. Their research sheds new light on whether and why social media content has predictive value for stock returns.

Frijns and Huynh (2018) were the first to demonstrate that media sentiment is an important external factor in analyst herding behavior. They studied the impact of media coverage on equity analyst herding behavior when recommending stocks, finding that analysts are more likely to exhibit herding behavior when media coverage shows pessimism about the company or when there is a high disagreement condition across media coverage. Ren and Wu (2020) proposed an innovative and forward-looking method to detect herding behavior of investors. They showed that there is real herding behavior in Chinese blue chips, and investors with pessimistic sentiment are more likely to follow the herd than those with optimistic sentiment, mainly due to the lack of fast and effective market information. Based on this, we propose Hypothesis 1 as follows.

H1. Social media sentiment triggers herd behavior in the stock market, and this herd behavior is irrational herd behavior.

As social media has become an increasingly popular way to access information, potentially false reports are commonplace on social media, and scholars have devoted significant research to the topic of social media credibility. Overall, authority and influence are important elements that constitute media credibility (Sterrett et al., 2019). The more authoritative the media is, the more likely it is to influence its readers. Liu and Li (2019) showed that the more authoritative the media following a financial event is, the more likely it is to amplify the influence of the financial event, which will also further intensify the spread of investor sentiment in financial networks. Official accounts in social media, under the role of government supervision, have high credibility of sources and rarely post inflammatory statements, which are less likely to trigger misleading and blindly following behavior among the public compared to the posting style of unofficial accounts. Therefore, we further propose Hypothesis 2 as follows.

H2. The sentiment of official social media accounts is not prone to irrational herd behavior of investors.

Sterrett et al. (2019) found that social media celebrities contribute significantly to the credibility of coverage. Follower size in social media platforms plays a crucial role in the ability of social media accounts to become opinion leaders. When social media users post information, even if the content posted is the same, the large number of followers will expand the influence of the article, increase the reach of the information, and more easily bring about the resonance of the information audience. Therefore, Hypothesis 3 is proposed as follows.

H3. For unofficial social media accounts, the larger the number of followers they have, the more likely it is to lead to irrational herding effects in the stock market.

In summary, the research framework of this study is shown in Fig. 2.

3. Methodology

3.1. Model for measuring herding

Herd behavior refers to the behavior of obeying the market consensus, imitating others' behavior and suppressing one's own ideas. Human psychology and social activity are highly correlated, and since stock market data reflects the investor decision-making behavior, it may not accurately capture psychological states due to measurement delays. Therefore, Ren's innovative sentiment analysis approach provides a more direct way to explore herd behavior, which has demonstrated its effectiveness. The emergence of herd behavior may be attributed to information cascades, where even a slight advantage in public information can cause people to follow market leaders while ignoring their own knowledge. We start by analyzing the roots of this psychological state, and suggest that for investors, widespread communication on social media can alleviate panic caused by information asymmetry to some extent. Stock price dispersion, which is measured by cross-sectional return standard deviation (Hwang & Salmon, 2004) and cross-sectional return absolute deviation (Chang et al., 2000), is a common empirical method used to examine herding behavior in the Chinese stock market. However, these models used stock market data as a measure of asset pricing, which presents a delay in reflecting the psychological state of our analysis subject, herd behavior. Asset prices can only reflect the results of investment behavior, which lags behind the occurrence of the psychological state to some extent. Therefore, the first problem that the model needs to overcome is the measurement delay. Based on this, Ren and Wu (2020) established an innovative measure of herding behavior based on investor sentiment by replacing stock price with an investor sentiment indicator. Since herd behavior is highly linked with human psychology, Ren and Wu (2020) used the cross-sectional absolute deviation of stock sentiment (CADS) as a measure of the degree of psychological dispersion. They argue that when herding behavior emerges, individual stock sentiment tends to market sentiment, i.e., investors have similar and less divergent opinions, and thus the deviation of individual investor stock sentiment from investor market sentiment can be used to capture the herding effect.

Following the work of Ren and Wu (2020), defining S_{it} as investor sentiment towards stock i at moment t, and S_{mt} as investor sentiment towards these K stocks at moment t, which is market sentiment, the relationship between them can be expressed as follows:

$$S_{it} = S_0 + \beta_i (S_{mt} - S_0) \tag{1}$$

where S_0 represents the basic market sentiment and β_i denotes the sentiment coefficient of the stock i. S_0 is usually set to 0 to represent that people hold neutral attitudes in practice. For market sentiment, based on the known individual stock sentiment S_{it}, the market sentiment S_{mt} can be calculated by referring to the construction method of China Central Television (CCTV) watch index as follows:

$$S_{mt} = \sum_{i=1}^{K} \omega_{it} \times S_{it} \tag{2}$$

where ω_{it} represents the weight of stock i on day t, which can be obtained by calculating the market value of stock i on day t as a percentage of the market value of all stocks in the sample data. The market sentiment coefficient β_m can be defined as follows, where K represents the number of stocks.

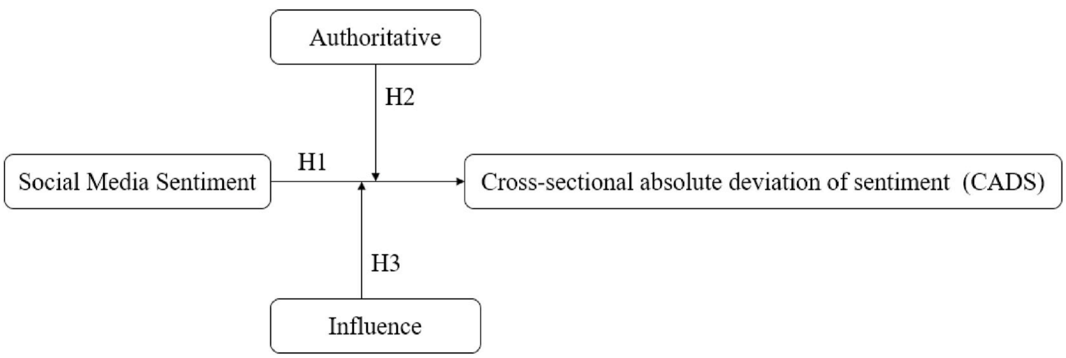

Fig. 2. Research frame.

$$\beta_m = \frac{1}{K}\sum_{i=1}^{K}\beta_i \tag{3}$$

Further, the absolute value of the deviation of investor sentiment from market sentiment for stock i (ADS_{it}) can be expressed as:

$$ADS_{it} = |(\beta_i - \beta_m)S_{mt}| \tag{4}$$

The cross-sectional absolute deviation of stock sentiment $CADS_t$ was calculated using the following equation:

$$CADS_t = \frac{1}{K}\sum_{i=1}^{K}ADS_{it} = \frac{1}{K}\sum_{i=1}^{K}|(\beta_i - \beta_m)S_{mt}| \tag{5}$$

$CADS_t$ can be used to measure the degree of sentiment bias. Ren and Wu (2020) showed that $CADS_t$ increases linearly with market sentiment in general.

$$\frac{\partial CADS_t}{\partial |S_{mt}|} = \frac{1}{K}\sum_{i=1}^{K}|\beta_i - \beta_m| > 0 \tag{6}$$

$$\frac{\partial^2 CADS_t}{\partial |S_{mt}|^2} = 0 \tag{7}$$

However, when herding behavior occurs, investors' individual stock sentiment and market sentiment converge, i.e., the relationship between $CADS_t$ and S_{mt} changes from a linear increasing relationship to a non-linear one, or if the herding effect is very severe, to a decreasing trend of $CADS_t$ with increasing S_{mt}. This allows further use of polynomial equations to measure herding behavior.

$$CADS_t = \alpha_1 + \lambda_1|S_{mt}| + \lambda_2(S_{mt})^2 + \delta_{1t} \tag{8}$$

If there is herd behavior in the stock market, investors' investment trend tends to follow the market trend, and investors' sentiment of investing in individual stocks will gradually converge to market sentiment, which is expressed in the regression equation as the magnitude of change in stock sentiment deviation is nonlinearly correlated with market sentiment, i.e., $\lambda_2(\lambda_2 < 0)$ is significant, or stock sentiment deviation will decrease as the absolute value of market sentiment increases, i.e., $\lambda_2 > 0$ but $\lambda_1(\lambda_1 < 0)$ is significant. If both λ_1 and λ_2 are negative and significant, there is a very significant herding behavior in the stock market.

In addition, identification of irrational herd behavior is achieved by including an asset control variable in the regression equation.

$$CADS = \alpha_2 + \lambda_3|S_m| + \lambda_4(S_m)^2 + \gamma_1 R_m + \delta_2 \tag{9}$$

If $\lambda_4(\lambda_4 < 0)$ is significant, or $\lambda_4 > 0$ but $\lambda_3(\lambda_3 < 0)$ is significant, we can conclude that herding behavior exists in the securities market, i.e., herding behavior remains when market returns change, then this herding behavior is not caused by the intrinsic value of assets and is irrational. If we can observe herding behavior in equation (8) but not in equation (9), this is a pseudo-herding behavior, i.e., the herding behavior at this point is driven by changes in asset value and can be called a rational herding behavior.

Based on the above CADS model (Ren & Wu, 2020), we introduce the social media sentiment variable SMS_t to construct a regression model to test the effect of social media sentiment on stock market herding effect.

$$CADS_t = \alpha_1 + (\lambda_1 + \theta_1|SMS_t|)|S_{mt}| + (\lambda_2 + \theta_2|SMS_t|)(S_{mt})^2 + \delta_{1t} \tag{Model-1}$$

$$CADS_t = \alpha_2 + (\lambda_3 + \theta_3|SMS_t|)|S_{mt}| + (\lambda_4 + \theta_4|SMS_t|)(S_{mt})^2 + \gamma_1 R_{mt} + \delta_{2t} \tag{Model-2}$$

In Model-1, if the coefficient value of $|S_{mt}|$ or $(S_{mt})^2$ is significantly negative. It indicates the existence of herding behavior in the stock market, which is explained in finance as people who would have held different preferences for each stock, but as the absolute value of market sentiment rises, people's preferences for all stocks converge, that is, $CADS_t$ decreases as $|S_{mt}|$ increases and decreases. It then indicates that herding behavior has occurred in the market. Since the CADS model (Ren & Wu, 2020) can discern the strength of the herding effect by the magnitude of the coefficient value of $|S_{mt}|$ or $(S_{mt})^2$, the smaller the value when the coefficient is negative, the more pronounced the herding behavior is, so if θ_1 is significantly positive on the basis of λ_1 being significantly negative, or θ_2 is significantly positive on the basis of λ_2 being significantly negative, it indicates that the intensity of social media sentiment will mitigate the herding effect in the stock market. Conversely, if both θ_1 and λ_1 are significantly negative, or both θ_2 and λ_2 are significantly negative, it indicates that social media sentiment intensity exacerbates the herding effect in the stock market.

Model-2 adds a control variable R_{mt} to Model-1 to identify irrational herding behavior. If the coefficient value of $|S_{mt}|$ or $(S_{mt})^2$ remains significantly negative, indicating that herding behavior continues to exist as stock returns change, then this herding behavior is not caused by intrinsic asset prices and it is a kind of irrational herding behavior. On this basis, the corresponding significantly negative θ_3 or significantly negative θ_4 indicates that social media sentiment exacerbates irrational herding behavior in the stock market.

3.2. Sample selection and data collection

3.2.1. Stock sample and data source

We select the Chinese SSE 50 constituent stocks as a sample to test herding behavior in the stock market. The SSE 50 is a sample of the 50 most representative stocks in the Shanghai stock market with large size and good liquidity, which comprehensively reflects the overall condition of a group of leading companies with the most market influence in the Shanghai stock market (Ren & Wu, 2020). These stocks are large-cap stocks, accounting for a large proportion of market capitalization. Their share prices will not be easily manipulated, and therefore are highly representative. Based on the above considerations, it is also reasonable to select the SSE 50 as a sample for the detection of irrational herding behavior in the stock market. The latest list of SSE 50 constituent stocks was obtained from the official website of the Shanghai Stock Exchange. The sample interval is 366 days and 243 trading days from January 1, 2020, to January 1, 2021. The individual stock sentiment S_{it} and SSE 50 market return R_{mt} of investors in the study were obtained from the China Stock Market & Accounting Research Database (CSMAR, https://cn.gtadata.com).

The investor sentiment index in the CSMAR database is obtained by processing the postings of investors in the Eastern Fortune and Sina stock forums. Stock forums, or investor communities, are platforms for investors to comment on the market and communicate information about individual stocks, and the main participants of stock forums are investors. Therefore, we use investor sentiment dispersion in the stock forum as a proxy variable for the herding effect.

3.2.2. Data collection for social media sentiment

Social media, an information dissemination medium in the Internet era, allows users to share information and opinions with each other, where the types of users include: institutions, celebrities, and ordinary users, among others. In other words, information about the characteristics of listed companies in social media not only represents the attitude of investors, but may also include media reports about companies, company information disclosures, or analysis suggestions of financial opinion leaders. Unlike stock forums, a broader range of people engaged in social media, constituting an information environment for investors and influencing their perceptions.

We use social media sentiment in the Sina Weibo platform as a research object to analyze its impact on investor sentiment. Sina Weibo is the largest, most active, and mainstream social media community in China, and a number of scholars have already used Sina Weibo text data to study the impact of media sentiment on the stock market (Duan, Liu, & Wang, 2021). We crawled a total of 247,708 data posted by authenticated users on the Sina Weibo platform for a total of 366 days from January 1, 2020 to January 1, 2021, using the names of 50 stocks in the SSE 50 as keywords. The composition of each data includes the hit keywords, posting media, posting content, posting time, number of followers and authentication type. One of the sample data with "Hengrui Medicine" as the keyword is shown in Fig. 3.

In the original data crawled, there are some noise and useless information. The noise information refers to web links, forwarded

Fig. 3. Data example from weibo platform.

contents, etc., and useless information refers to the reports about "China University of Petroleum" crawled with "China Petroleum" as the keyword, the sales advertisements of various Unicom business halls crawled with "China Unicom" as the keyword, etc., which are not related to the listed company referred to by the keyword. If these noisy and useless information are not handled, it will bring large bias to the social media sentiment analysis results. Therefore, this study preprocesses the data in the Python environment with the help of regular expressions, removes the noise in the text information, as well as the postings of various marketing numbers and irrelevant direction users, and finally integrates 227,353 valid posts. Among these posts, 23,981 social media accounts are included, and their number of fans is between 0 and 185,227,678.

When calculating investor sentiment, we adopt the same variable calculation method as Ren et al.'s research. We obtain data on investor sentiment from stock investment forums through CSMAR (China Stock Market & Accounting Research Database), which is a database (https://cn.gtadata.com/). In summary, the data used in the model of this study and their sources are shown in Table 1.

3.3. Variable operation

3.3.1. Social media sentiment

We perform sentiment analysis on the social media data obtained from Weibo to construct daily social media sentiment time series data. Sentiment analysis involves automatically identifying sentiments, evaluations, attitudes, and emotions from unstructured text data. Text sentiment analysis is an important branch in the field of natural language processing, which is divided into sentiment analysis methods based on sentiment dictionaries and sentiment analysis methods based on machine learning and deep learning.

Ren and Wu (2020) used a lexicon-based approach for sentiment analysis. The sentiment lexicon-based identification method was the first text sentiment analysis method to emerge, and the principle of this method is to use the sentiment words in the domain sentiment lexicon in which the text data is located to match the sentiment words in the text to be analyzed, and then score these matched sentiment words, and finally accumulate the sentiment word score, which then represents the sentiment intensity value of the text and the sentiment tendency of the text to be analyzed. The sentiment lexicon-based approach can accurately reflect the unstructured features of the text and is easy to analyze and understand. In this method, the sentiment classification effect is more accurate when the coverage and accuracy of sentiment words are high. However, this method has certain shortcomings: The method mainly relies on the construction of sentiment dictionaries, but due to the rapid development of the network and the speed of information updates, many new words emerge on the network. Hence, it does not perform well with respect to recognizing of many new words, including hysterics, idioms, and special terms on the Internet. This means that, existing sentiment dictionaries need to be constantly expanded to meet the needs. Meanwhile, the same sentiment word in the sentiment dictionary may have different meanings in different situations, languages or domains; hence, a lexicon-based method would not be very effective in cross-domain and cross-linguistic applications. On the other hand, the semantic relationship between contexts might be ignored. Thus, in our study, we consider improving sentiment analysis methods.

Machine learning is method that trains a model from given data and predicts the results of the model. The method has been studied by numerous researchers, and many effective results have been achieved. A machine learning-based sentiment analysis method refers to the use of statistical machine learning algorithms to extract features from a large amount of annotated or unannotated corpora, and then finally perform sentiment analysis to output the results. The machine learning approach transforms the problem of text sentiment analysis into a problem of text classification, and achieves the final sentiment tendency analysis by classifying the text through feature learning. Compared with the sentiment lexicon method, the method has stronger generalization ability. In terms of applicability, the number of words in a single posting on social media such as microblogs must not exceed 140, and the content of written expressions may also be full of emojis, networked language, colloquial expressions, and misspellings. The above problems are bottlenecks in the sentiment lexicon method for dealing with text sentiment, which can lead to unsatisfactory accuracy of the final analysis. In contrast, the machine learning method is considered to be more effective in discriminating semantic contexts and recognizing textual attitudes, but the limitation of this method is that it relies on the quality of the training set and classifier.

Based on the above analysis, the sentiment analysis method constructed in this paper is based on the idea of supervised learning sentiment analysis method in natural language processing techniques.

1) Sentiment Analysis Based on Natural Language Processing

First, we build a training set and a test set with emotion triple classification labels. The classifier then learns its potential. Finally, the emotion classification effect of the classifier is evaluated, and the prediction results of the classifier with better effect are selected.

Table 1
Description of variables.

Variable	Description	Method	Source
S_{it}	Investor sentiment of individual stocks	Database	CSMAR
ω_{it}	Market capitalization of stock i on day t as a percentage of the market capitalization of all stocks in the sample	Database	CSMAR
S_{mt}	Market Sentiment	Calculation	Equation 2
$CADS_t$	Cross-sectional absolute dispersion of investor sentiment	Calculation	Equations (1)–5)
SMS_t	Social media sentiment	Calculation	Equation (10)-12)
R_{mt}	SSE 50 Index Market Return	Database	CSMAR

The classifiers selected in this paper are support vector machine model (SVM) based on machine learning idea, long short-term memory network model (LSTM) based on deep learning idea, and BERT model based on migration learning idea. The process of sentiment analysis is shown in Fig. 4.

Specifically, we first sort all text data in the exact mode of the Jieba sorter package. Its exact mode can slice and dice words, and each word will only appear in one word, which is suitable for text analysis. Certain words or symbols that are automatically ignored in the word separation process are called deactivated words, which usually appear repeatedly in the text but do not contribute a clear meaning, and by filtering deactivated words, keyword density can be effectively improved. In the process of word separation, the deactivated word list of Harbin Institute of Technology was added, and on the basis of it, deactivated words with high frequency but low contribution, such as "lunch commentary," "headline article," and "real-time broadcast," which are closely related to the text of this study, were added to obtain more valuable word separation data.

Subsequently, 40,000 texts were randomly selected for manual sentiment labeling. The sentiment was divided into three categories: optimistic, neutral, and pessimistic. If the text expresses the joy of the stock's big rise or is bullish about the stock's future trend, it is marked as optimistic. If the text expresses disappointment about the stock's dive or thinks the stock is not worth investing, it is marked as pessimistic. If the sender does not analyze the stock or interpret the stock market information with personal subjective emotion, it is marked as neutral emotion. Among the 40,000 labeled texts, optimistic texts accounted for 14,816, neutral texts accounted for 15,855, and pessimistic texts accounted for 9329.

Further, the labeled data were sliced into training data and test data in the ratio of 8:2. A total of 32,000 training data were obtained, which contained 11,863 optimistic sentiment data, 12,684 neutral sentiment data, and 7463 pessimistic sentiment data. A total of 8000 test data were obtained, which contained 2953 optimistic sentiment data, 3171 neutral sentiment data, and 1866 pessimistic sentiment data. We adopted three classifiers based on the ideas of machine learning, deep learning and migration learning, SVM, LSTM, and BERT, respectively, to analyze the sentiment of the remaining 187,353 pieces of unlabeled data.

2) Evaluation of Sentiment Analysis

After completing the sentiment classification using the constructed text classifier, we compare the classification results of these three classifiers, as shown in Table 2.

From the experimental results presented in Tables 2 and it can be concluded that among the sentiment classification models, SVM and BERT perform relatively similar in terms of accuracy, differing in that SVM has higher accuracy for pessimistic class prediction and lower accuracy for optimistic class prediction, while BERT shows the opposite. The most impressive performance is LSTM, which outperforms SVM and BERT in most of the performance evaluation metrics of accuracy, recall, F1 score, precision, macro-average, and weighted average. The 91% accuracy of LSTM is 3% higher than that of SVM and LSTM.

Based on the above analysis, LSTM is selected as the final sentiment classifier in our study, and its sentiment prediction results are used as the sentiment of unlabeled text for social media reports. The final classification results obtained are shown in Fig. 5.

3) Social Media Sentiment Index

We construct social media sentiment, i.e., textual sentiment posted daily, for empirical analysis with stock index data to investigate whether social media sentiment affects irrational herd behavior in the stock market. In this paper, building on Liang et al. (2020) and Checkley, Higon, and Alles (2017), we construct social media sentiment as follows:

$$SMS_t = \sum_{i=1}^{N} \omega_{i,t}\ Sentiment\ t_{i,t} \tag{10}$$

$$Sentiment\ t_{i,t} = \ln\left(\frac{1+Pos_{i,t}}{1+Neg_{i,t}}\right) \tag{11}$$

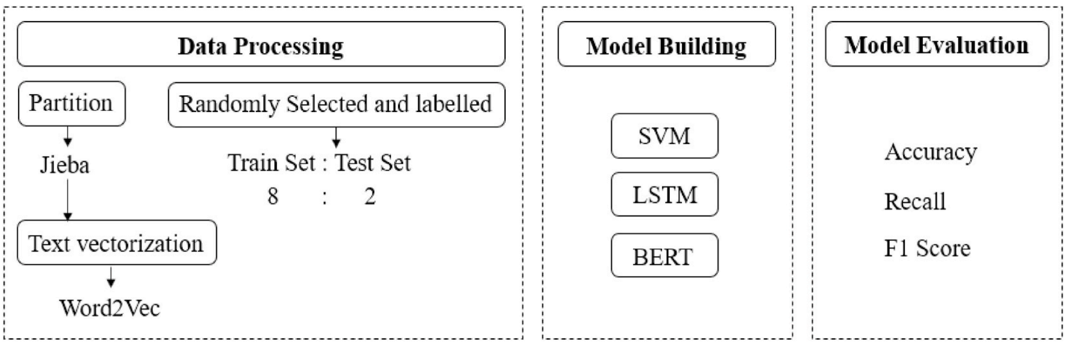

Fig. 4. Text data sentiment analysis process.

Table 2
Model evaluation of SVM, LSTM and BERT.

Model		Precision	Recall	F1 Score
SVM	Optimistic	0.89	0.75	0.81
	Neutral	0.89	0.90	0.90
	Pessimistic	0.86	0.94	0.90
	Accuracy	/	/	0.88
	Macro average	0.88	0.86	0.87
	Weighted average	0.88	0.88	0.88
LSTM	Optimistic	0.94	0.89	0.92
	Neutral	0.90	0.94	0.92
	Pessimistic	0.89	0.92	0.90
	Accuracy	/	/	0.91
	Macro average	0.91	0.92	0.91
	Weighted average	0.91	0.91	0.91
BERT	Optimistic	0.86	0.94	0.90
	Neutral	0.90	0.87	0.88
	Pessimistic	0.91	0.80	0.85
	Accuracy	/	/	0.88
	Macro average	0.89	0.87	0.88
	Weighted average	0.89	0.88	0.88

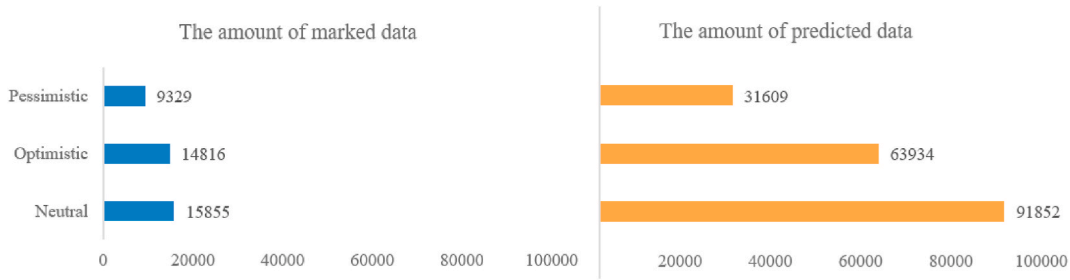

Fig. 5. Number of posts in each emotion category.

$$\omega_{i,t} = \frac{MV_{i,t}}{\sum_{i=1}^{N} MV_{i,t}} \tag{12}$$

where SMS_t represents the social media sentiment on day t, N represents the number of stocks included in the data, which is 50; and *Sentiment* $t_{i,t}$ represents the sentiment index of stock i on day t. $Pos_{i,t}$ represents the number of tweets with positive sentiment posted by stock i on day t, and $Neg_{i,t}$ represents the number of tweets with pessimistic sentiment posted by stock i on day t. $\omega_{i,t}$ represents the market value share of stock i on day t, and $MV_{i,t}$ represents the market value of stock i on day t.

Equation (12) shows that if *Sentiment* $t_{i,t} > 0$, it represents the optimistic sentiment of stock i's tweets on day t, and the larger *Sentiment* $t_{i,t}$ indicates the higher optimism, while *Sentiment* $t_{i,t} < 0$ represents the pessimistic sentiment of stock i's tweets on day t, and the smaller *Sentiment* $t_{i,t}$ indicates a higher degree of pessimism. Equation (10) is based on equation (11), and $SMS_t > 0$ means the overall optimistic sentiment of tweets on day t, and the larger SMS_t indicates the higher optimistic degree.

3.3.2. Cross-sectional absolute deviation of investors' sentiment

Investors' individual stock sentiment S_{it} is obtained from the CSMAR database. In the market information series of the CSMAR database, we could obtain the investor sentiment index directly, which is calculated by using deep learning models to judge the text of stock commentaries in stock forums (Eastern Fortune and Sina stock forums), and compile the sentiment and opinion attitude of stock commentaries of each listed company, providing quantitative public opinion data categorized and counted by listed companies.

Table 3
Descriptive statistics of variables.

	Mean	Min	Median	Max	SD	Skewness	Kurtosis
$CADS_t$	0.243	0.118	0.214	0.572	0.093	1.537	1.896
S_{mt}	−0.064	−0.600	−0.074	0.313	0.128	0.270	0.993
R_{mt}	0.001	−0.070	0.001	0.068	0.014	−0.296	4.918
SMS_t	0.302	−0.552	0.315	1.328	0.344	−0.046	−0.034

Therefore, we employ the index of investors' sentiment to represent S_{it}. Further, $CADS_t$ can be calculated according to equations (1)–(5).

3.3.3. Variable statistics

According to the calculation above, the statistics of key variables in the model are shown in Table 3. These include the cross-sectional absolute deviation of investor sentiment $CADS_t$ and market sentiment S_{mt} based on investor sentiment on individual stocks, SSE50 market return R_{mt} (obtained directly from the CSMAR database), and the social media sentiment variable SMS_t constructed in Section 3.3.1.

4. Empirical results

4.1. The impact of social media sentiment on herding behavior

4.1.1. Statistical analysis and stability tests

Since our study is concerned with whether there is a nonlinear relationship between investor sentiment deviation *CADS* and market sentiment S_m in the model studying the effect of social media sentiment on stock market herding behavior, in order to first observe the relationship between the two intuitively, a scatter plot is depicted for preliminary judgment. Fig. 6 shows that there is no obvious linear relationship between *CADS* and S_m regardless of whether market sentiment is high or low, i.e., whether market sentiment is less than 0 or greater than 0. The shape of the scatter distribution indicates that there is likely a quadratic nonlinear relationship between the two. Moreover, according to the definition of *CADS* indicator, if there is herding behavior in the stock market, the change of individual stock sentiment S_i and market sentiment S_m will converge, which means that the CADS value will gradually shrink as the absolute value of market sentiment $|S_m|$ becomes larger and finally converge to 0. This is also clearly reflected in the scatter plot. The above preliminary interpretation and analysis of the scatter diagram suggests that there is likely to be herd behavior of investors driven by sentiment in the blue-chip market.

Before conducting the empirical study, the time series data must be tested for stability to eliminate the effect of time data trend and avoid the pseudo-regression problem. We use ADF test for investor sentiment deviation *CADS*, market sentiment S_m and market return R_m as shown in Table 4. The unit root tests for all variables selected are significant at the 1% level, indicating that the three sets of time series data are stationary over the sample period.

4.1.2. Results

We test the relationship between social media sentiment and herd behavior according to Model-1 and Model-2. Table 5 summarizes the regression analysis results. In Model-1, the coefficient value of $|S_{mt}|$ is $(-0.335–0.995\ |SMS_t|)$ and is significantly negative, indicating that there is a significant herding effect in the stock market, wherein investor sentiment bias decreases as the absolute value of market sentiment increases and a convergence situation occurs. The coefficient corresponding to $|SMS_t| \cdot |S_{mt}|$ is also significantly negative, which also proves that the intensity of social media sentiment exacerbates the herding behavior in the Chinese stock market. In Model-2, by adding the control variable R_{mt}, we can distinguish whether the herding behavior is caused by asset value. The results show that the coefficient of $|S_{mt}|$ is still significantly negative, which indicates that the herding behavior is not caused by R_{mt}; this herding behavior is a kind of irrational herding behavior. The coefficient of $|SMS_t| \cdot |S_{mt}|$ is also significantly negative, which indicates that social media sentiment intensity enhances this irrational herding effect in the stock market.

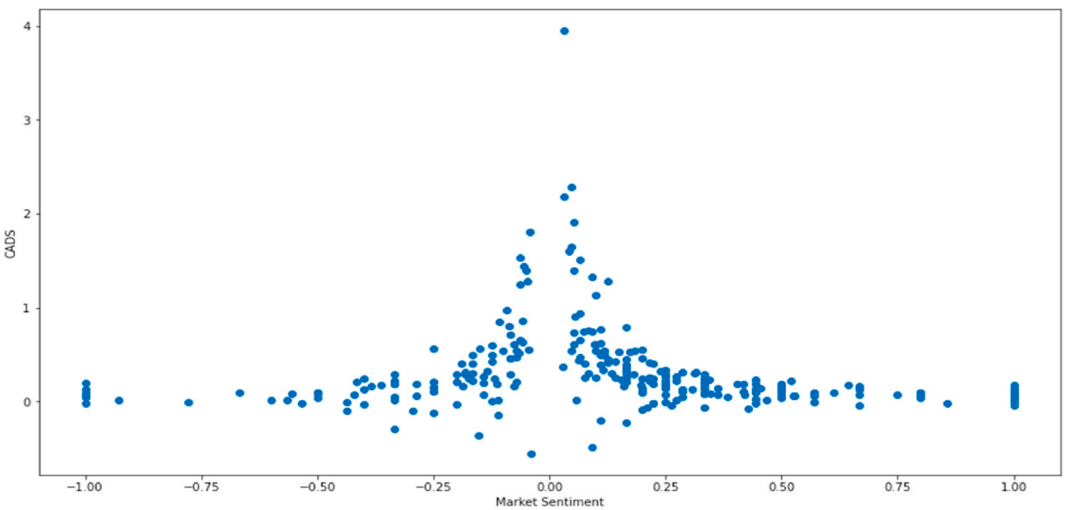

Fig. 6. Scatter plot of *CADS* and S_m.

Table 4
Stability test of $CADS, S_m$ and R_m
*p < 0.1, **p < 0.05, ***p < 0.01

	$CADS$	S_m	R_m
T-statistic	−14.14199***	−12.69933***	−13.61207***
P value	0.0000	0.0000	0.0000

Table 5
Regression results for social media sentiment on herd behavior.
This table contains regression analysis for a total of 243 trading days during the period from January 1, 2020 to December 31, 2020. Where S_{mt} is the market sentiment constructed based on investors' individual stock sentiment S_{it} (the calculation procedure is shown in Equation (2)), SMS_t is the social media sentiment index, and the calculation procedure is Equation 10-Equation (12). R_{mt} is the SSE 50 market return. Column1 reports the results of the regression test based on Model-1, and Column2 reports the results of the regression test based on Model-2.
*p < 0.1, **p < 0.05, ***p < 0.01

Variables	Column 1: Model −1	Column 2: Model −2
cons	0.277***	0.272***
	(21.765)	(21.079)
$\lvert S_{mt}\rvert$	−0.335**	−0.315*
	(-1.972)	(-1.858)
$\lvert SMS_t\rvert \cdot \lvert S_{mt}\rvert$	−0.995**	−0.951**
	(-2.271)	(-2.175)
$(S_{mt})^2$	0.264	0.481
	(0.529)	(0.939)
$\lvert SMS_t\rvert \cdot (S_{mt})^2$	5.880***	5.191***
	(3.284)	(2.842)
R_{mt}		0.842*
		(1.738)
N	243	243
Adjusted R^2	0.075	0.083

The evidences from Table 5 are consistent with Hypothesis 1, showing that social media sentiment affects irrational herd behavior in the stock market. We can assume that people in the stock market refer to social media messages and are influenced by text sentiment to abandon their own ideas and follow the group consensus, generating irrational herd behavior.

Table 6
Robustness checks for social media sentiment on herd behavior.
This table contains regression analysis for a total of 243 trading days during the period from January 1, 2020 to December 31, 2020. Where S_{mt} is the market sentiment constructed based on investors' individual stock sentiment S_{it} (the calculation procedure is shown in Equation (2)), SMS_t is the social media sentiment index, and the calculation procedure is Equation (10), Equation (12), and Equation (13). R_{mt} is the SSE 50 market return. Column1 reports the results of the regression test based on Model-1, and Column2 reports the results of the regression test based on Model-2.
*p < 0.1, **p < 0.05, ***p < 0.01

Variables	Column1: Model −1	Column2: Model −2
cons	0.273***	0.270***
	(22.144)	(21.511)
$\lvert S_{mt}\rvert$	−0.262	−0.270
	(-1.490)	(-1.535)
$\lvert SMS_t\rvert \cdot \lvert S_{mt}\rvert$	−1.920**	−1.757**
	(-2.222)	(-2.021)
$(S_{mt})^2$	−0.306	−0.033
	(-0.518)	(-0.053)
$\lvert SMS_t\rvert \cdot (S_{mt})^2$	13.268***	11.753***
	(3.449)	(2.957)
R_{mt}		0.693
		(1.461)
N	243	243
Adjusted R^2	0.091	0.095

4.1.3. Robustness checks

In Ren and Wu (2020) study, the sentiment analysis was more focused on the use of positive and negative words due to author's adoption of sentiment lexicon matching. In contrast, the sentiment index we use is constructed using a machine learning classification algorithm; hence, we also use a different formula for calculating the social media sentiment index (i.e., Equation (11)).

For this reason, we further examine the bias introduced by the different calculations regarding social media sentiment to verify the robustness of our above results. In Ren and Wu (2020) 's study, social media sentiment is calculated as follows:

$$Sentiment\ t_{i,t} = \frac{2Pos_{i,t}}{Pos_{i,t} + Neg_{i,t}} - 1 \tag{13}$$

where *Sentiment* $t_{i,t}$ represents the sentiment index of stock i on day t. $Pos_{i,t}$ represents the number of posts with positive sentiment posted by stock i on day t, and $Neg_{i,t}$ represents the number of posts with negative sentiment posted by stock i on day t. The time series sentiment index *Sentiment* $t_{i,t}$ is computed from equation (13) and varies within the range between −1 and 1. When *Sentiment* $t_{i,t} > 0$, it indicates that people take a positive attitude, and when *Sentiment* $t_{i,t} < 0$, it indicates that people hold a negative stance.

Table 6 summarize the results of the robustness checks. In Model-1, the coefficient of $|S_{mt}|$ is insignificant, indicating that investor sentiment bias does not appear to converge with market sentiment at this time. However, the coefficient of $|SMS_t| \cdot |S_{mt}|$ is significantly negative, reflecting that the intensity of social media sentiment affects the herding behavior of the stock market. In Model-2, the results show that the herding behavior is not caused by R_{mt}, then this herding behavior is an irrational herding behavior. Further, the coefficient of $|SMS_t| \cdot |S_{mt}|$ is significantly negative, indicating that the social media sentiment intensity enhances this irrational herding effect in the stock market. Thus, when we use different time-series calculations of social media sentiment, the evidence from Table 6 still confirms that social media sentiment affects irrational herding behavior in the stock market.

4.2. The effect of social media authority on herd behavior

The content of information issued by sources with different degrees of authority can differ in terms of authenticity, objectivity, and impartiality. Officiality tends to be a proxy variable for the degree of authority. The statements made by official issuers may be more objective, while unofficial issuers may lack impartiality in their expressions and issue reports that exaggerate the reality in order to attract public attention. Thus, official and unofficial releases may have different impacts on investors' psychology through textual sentiment, which in turn may affect investor behavior.

We further verify the differences in the effects from official accounts based on the group regressions. In Table 7, Panel A shows the test results of social media sentiment in official accounts on herding behavior and finds that the coefficient value of $|SMS_t| \cdot |S_{mt}|$ is not significant. The coefficient value of $|SMS_t| \cdot (S_{mt})^2$ is positive, indicating that official accounts' sentiment does not affect investors' herding behavior, much less their irrational herding behavior. However, unlike in Panel B, it can be observed that the coefficient values of $|S_{mt}|$ and $|SMS_t| \cdot |S_{mt}|$ are significantly negative, which indicates that the intensity of unofficial accounts' sentiment exacerbates irrational herding behavior. Therefore, Hypothesis 2 is supported.

We further analyze the reasons for the influence of official accounts. First, in terms of sentiment, the standard deviation of social media sentiment is 0.187 for official accounts and 0.342 for unofficial accounts, which is relatively more stable, indicating that the

Table 7

Regression results for official social media sentiment on herd behavior.

This table contains regression analysis for a total of 243 trading days during the period from January 1, 2020 to December 31, 2020. Where S_{mt} is the market sentiment constructed based on investors' individual stock sentiment S_{it} (the calculation procedure is shown in Equation (2)), SMS_t is the social media sentiment index, and the calculation procedure is Equation 10-Equation (12). R_{mt} is the SSE 50 market return. Panel A reports the regression test results for official accounts, and panel B reports the regression test results for unofficial accounts.

*p < 0.1, **p < 0.05, ***p < 0.01

Variables	Panel A: Official accounts		Panel B: Unofficial accounts	
	Model −1	Model −2	Model −1	Model −2
Cons	0.272***	0.266***	0.276***	0.272***
	(21.264)	(20.540)	(21.816)	(21.129)
$\|S_{mt}\|$	−0.418**	−0.386**	−0.334*	−0.322*
	(-2.517)	(-2.339)	(-1.967)	(-1.901)
$\|SMS_t\| \cdot \|S_{mt}\|$	−1.155	−1.026	−0.964**	−0.900**
	(-1.492)	(-1.333)	(-2.174)	(-2.030)
$(S_{mt})^2$	0.829*	1.044**	0.240	0.467
	(1.852)	(2.304)	(0.476)	(0.897)
$\|SMS_t\| \cdot (S_{mt})^2$	7.372**	5.759*	5.897***	5.157***
	(2.221)	1.712	(3.232)	(2.755)
R_{mt}		1.098**		0.803*
		(2.301)		(1.663)
N	243	243	243	243
Adjusted R^2	0.042	0.059	0.076	0.083

content of official accounts does not show large emotional fluctuations that bring psychological stimulation and misinformation to readers. Unofficial accounts, on the other hand, may have more extreme emotions, which are more likely to have an impact on the audience's investment psychology and intensify the irrational herd behavior in the stock market.

Second, in terms of the number of reports, the total number of articles posted by official accounts is 14,261, while the number of articles posted by unofficial accounts is 213,134, with a ratio of nearly 1:15. The greater the number of posts, the greater the possibility of article exposure, since the audience is more bombarded with information coupled with the non-objective tone of unofficial accounts, the audience is more likely to form a cognitive bias about the direction of the stock market and generate irrational behavior driven by the seemingly extremely excellent or extremely poor market investment environment.

4.3. The effect of social media Account's influence on herd behavior

The influence of social media accounts can have a different impact on the audience. When the influence of a social media account is higher, its statements are more likely to be trusted and followed by the public, which in turn affects group decisions. The more followers a social media account has, the more attention it receives, and the exposure of an article has a direct positive correlation with the number of followers. In addition, followers' attention behavior mainly comes from followers' recognition and favoritism, so the higher the recognition and favoritism of an account, the higher the possibility of its blog posts being retweeted, and the more likely it is to bring about strong public opinion; hence, there is a potential positive correlation between article exposure and followership in terms of retweeted articles.

In the inquiry about the authority of social media accounts on herd behavior, it can be found that official posting sentiment does not easily affect herd behavior. However, unofficial posting sentiment affects irrational herd behavior in the stock market, most likely because unofficial accounts gain the attention of followers by exaggerating facts and over-dramatizing for their own benefit to get followers' attention. We then analyze the fan effect of unofficial social media accounts, and we divide the unofficial social media accounts in the sample data into intervals based on the number of followers, as shown in Table 8.

Table 9 reports the results of herd behavior for different fan number categories. In Panel A, for accounts with less than 10,000 followers, the coefficient values of $|SMS_t| \cdot |S_{mt}|$ are not significant, indicating that their stock market-related posts do not affect stock market herding behavior in terms of sentiment, probably due to the weak influence of such accounts that do not easily gain the trust and empathy of their followers. As a result, the sentiments revealed in the tweets are not fully received and recognized by the audience, and therefore do not easily influence their behavior.

When the number of followers is greater than 10,000 but less than 1,000,000, social media sentiment intensity has a significant effect on stock market irrational herd behavior. The impact brought by social media sentiment becomes more obvious with the increase of follower magnitude, which can be reflected by the significant degree of the coefficient value of $|SMS_t| \cdot |S_{mt}|$, and the degree of impact brought by social media sentiment intensity on the herding effect has increased significantly.

Panel B illustrates on the one hand that the rise in the number of followers does bring about an increase in the account's influence, and social media sentiment has a guiding and effect on investment behavior. On the other hand, the existence of irrational herd behavior also indicates that unofficial postings do not change their own investment behavior when a change in asset value occurs, but change their own investment behavior under the rendering and guidance of sentiment. This is consistent with Hypothesis 3.

More interestingly, when the number of followers continues to increase beyond 1 million, social media sentiment no longer influences investors' herding behavior, which contradicts Hypothesis 3. It is not that the continued growth in the number of followers leads to a more prominent herding effect, but rather that the effect of social media sentiment on the herding effect disappears when the number of followers reaches a certain critical value. This is likely because social media accounts with more than 1 million followers, as the opinion leaders of the platform, no longer use exaggerated reports to attract public attention in order to maintain their status and image, but instead produce more valuable investment advice, and thus are less likely to induce biased sentiment in the stock market and lead irrational herd behavior.

5. Discussion

The main reason for herd behavior is the existence of an information cascade, meaning the advantage of public information is enough to cause people to follow the market leader and ignore their own knowledge (Bikhchandani & Sharma, 2001). Another explanation is the "animal spirits" of humans. The term "animal spirits" was first coined by Keynes (1937)and then developed as a measure of whimsical variations in people's views or emotions. Hence, in contrast to other studies measuring herd behavior, this study continues the work of Ren and Wu (2020) by describing psychological states and capturing people's psychological states using investor sentiment as a path. This avoids incorrect and delayed effects compared with measuring herd behavior using stock market trading data

Table 8
Distribution of number of fans of unofficial accounts.

Number of fans interval	Number of unofficial accounts in the interval	Percentage of all unofficial account numbers
Less than 10,000	54,192	25.43%
10,000 to 100,000	47,663	22.36%
100,000 to 1 million	76,898	36.08%
More than 1 million	34,381	16.13%

Table 9
Regression results for unofficial accounts' influence on herd behavior.
This table contains regression analysis for a total of 243 trading days during the period from January 1, 2020 to December 31, 2020. Where S_{mt} is the market sentiment constructed based on investors' individual stock sentiment S_{it} (the calculation procedure is given in Equation (2)), SMS_t is the social media sentiment index, and the calculation procedure is given in Equation (10) - Equation (12). R_{mt} is the SSE 50 market return. Panel A reports the regression test results based on Model-1, and Panel B reports the regression test results based on Model - 2 regression test results.
*p < 0.1, **p < 0.05, ***p < 0.01

	Panel A: Model −1			
	Number of fans <10,000	Number of fans 10,000–100,000	Number of fans 100,000–1 million	Number of fans >1 million
Cons	0.273***	0.274***	0.274***	0.266***
	(21.902)	(21.873)	(21.819)	(21.683)
$\|S_{mt}\|$	−0.046***	−0.345**	−0.322**	−0.226
	(-0.257)	(-2.001)	(-1.897)	(-1.254)
$\|SMS_t\|\cdot\ \|S_{mt}\|$	−1.783	−1.154*	−1.045**	−1.386
	(-3.557)	(-1.911)	(-2.043)	(-1.631)
$(S_{mt})^2$	−0.575	0.288	0.116	0.118
	(-0.954)	(0.564)	(0.218)	(0.205)
$\|SMS_t\|\cdot\ (S_{mt})^2$	8.038***	7.495***	6.876***	7.926**
	(3.683)	(2.972)	(3.111)	(2.358)
N	243	243	243	243
Adjusted R^2	0.064	0.069	0.078	0.051
	Panel B: Model −2			
	Number of fans <10,000	Number of fans 10,000–100,000	Number of fans 100,000–1 million	Number of fans >1 million
Cons	0.267***	0.269***	0.270***	0.263***
	(21.218)	(21.184)	(21.273)	(21.294)
$\|S_{mt}\|$	−0.065***	−0.343**	−0.314*	−0.238
	(-0.370)	(-2.000)	(-1.859)	(-1.332)
$\|SMS_t\|\cdot\ \|S_{mt}\|$	−1.591	−1.010*	−0.989**	−1.288
	(-3.171)	(-1.665)	(-1.940)	(-1.525)
$(S_{mt})^2$	−0.070	0.557	0.355	0.452
	(-0.111)	(1.051)	(0.647)	(0.763)
$\|SMS_t\|\cdot\ (S_{mt})^2$	6.524***	6.279**	6.115***	6.668**
	(2.909)	(2.417)	(2.728)	(1.969)
R_{mt}	1.191**	0.858*	0.839*	1.033**
	(2.496)	(1.811)	(1.778)	(2.170)
N	243	243	243	243
Adjusted R^2	0.084	0.078	0.086	0.065

(Chang et al., 2000; C. R. D. Huang, 1995).

Qualitative information plays an important role in the stock market, and it includes news articles, press releases, and stock forums (Ghidini, Di Francescomarino, Rospocher, Tonella, & Serafini, 2012; Wu, Zheng, & Olson, 2014). Investors rely on the information provided on social media to make investment decisions. In this process, the emotions contained in the information affect investors' psychology, which in turn affects their degree of absorption and perception of the information, and finally guides their decision-making behavior. In the case of asymmetric market information of individual investors, they are more likely to be irrationally driven by social media sentiment, follow the advice of social media information, and follow the trading decisions of other investors, which in turn generates the herding effect in the stock market. The empirical results of this paper also show that social media sentiment can influence the limited rationality of stock market investors.

Further, this study extends the existing research on the heterogeneity of social media accounts. Accounts with authority have the ability to generate high-quality, unbiased information and are therefore less likely to lead to cognitive biases and irrational behavior. For the public, they can reduce the negative impact of false information and misinformation on investment decisions by focusing on the authority of the information source. When people are confused about which accounts can provide accurate information, social media can present clearer signs of sources for users.

In addition, social media messages are noticed and popular because influential communicators share their messages with their followers and the public tends to listen to accounts they trust and approve of. Communicators with larger fan bases pay attention to the accuracy and authenticity of information before disseminating it to their followers, because accounts with large social media audiences have a greater responsibility to verify the value of any information to be shared. Accounts with smaller followers, on the other hand, may be more prone to discursive misconduct, in part because they are more unprofessional or less cautious and prone to unconsciously express biased views.

As Internet technologies evolve, social media data present conceptual, computational, and ethical challenges that require our scientific theories to be reinvigorated to keep pace with rapidly changing social realities and our ability to capture them. The findings in this paper theoretically enrich the study of behavioral finance and narrative economics; we need new ways of managing, using, and analyzing data (Lazer et al., 2021). Our research will hopefully give good insights into the proper understanding of the relationship between social media sentiment and investor behavior. Since a herding effect is one of the indicators of potential systemic risk (Dhaene, Linders, Schoutens, & Vyncke, 2012), governments and regulators need to monitor this phenomenon in real time. Specifically, inefficiencies in information disclosure and the inherent properties of suspicion and imitation of humans may be behind this issue. Thus, regulators and companies have a responsibility to improve information transparency and create a level playing field for investors.

Social media represent an important channel through which retail investors become more informed, and many studies proposed that emotions expressed on social media have the ability to predict stock prices (Da, Engelberg, & Gao, 2011). Previous research has shown that information differences are more important for trading than differences across market approaches. Nearly a quarter of American adults rely on investment advice from social media. Meanwhile, regulatory agencies have pointed out that social media is changing the landscape and its relevance to the financial markets is only increasing (Chen, De, Hu, & Hwang, 2014). Numerous studies have examined the relationship between social media and financial investment behavior. We propose that the herd effect in investment behavior is the driving force behind this predictable phenomenon. Ren and Wu (2020)explored the impact of investor sentiment on herd behavior using data from investor comments in stock forums. As social media usage continues to grow, it is used by a wider and more diverse range of people, with greater dissemination efficiency and influence than expert advice in stock forums. We aim to identify differences in the impact of herd behavior through social media sentiment and to expand the boundaries of behavioral finance research by exploring the identification of the herd effect in investment behavior.

6. Conclusion

This study conducts research based on posts-related data in Weibo. After comparing different sentiment classification methods, we select the classification results of the LSTM model as text sentiment to construct social media sentiment indicators reflecting daily psychological fluctuations. Finally, we explore the relationship between social media sentiment and stock market herd behavior using the CADS model to test whether the influenced herd behavior is irrational and to examine the differential impact brought by social media accounts on herd behavior. First, the study examines the relationship between social media sentiment, as measured by tone, and stock market herding behavior tendencies in terms of investors' psychological and cognitive patterns, and finds that social media sentiment brings about a guiding effect on investors' herding motives. Second, we identify whether stock market herding behavior influenced by sentiment is irrational, and illustrate with empirical results that social media sentiment can influence the degree of rationality of stock market investors. Finally, based on media credibility theory, the study analyzes the differentiation of social media officialness and followership on the influence of herd behavior. The results show that the sentiment of official social media accounts has no significant effect on stock market herding behavior, while the sentiment of unofficial social media accounts with larger fan bases is more likely to influence irrational herding behavior in the stock market, but there is a certain threshold for this fan magnitude effect.

Although this study provides some insights into the social media sentiment in identifying herding behavior, some limitations need to be addressed through follow-up studies. First, subsequent work can be extended to conducting the study from a richer sample of stocks and a broader time horizon to provide more representative results. Second, our study only classifies emotions into optimistic, neutral, and pessimistic categories, while in recent years emotion classification techniques have been refined to the level of distinguishing emotion categories with fine granularity, and subsequent consideration can be given to further refining emotions into anger, joy, disgust, surprise, and trust, etc., to more carefully examine the impact of social media sentiment factors on stock market herd behavior, as well as explore the nonlinear relationships and interactions between sentiment categories. Third, presenting causal relationships of research variables is extremely challenging but highly convincing, and establishing a causal analysis structure between social media sentiment and stock market herd behavior within the framework of the CADS model would also be very meaningful work, it is worth expanding the analysis further.

Classical financial theory did not account for investor sentiment and assumed that asset prices reflected the rational discounted values of rational investors. In their view, even if some investors were irrational, arbitrageurs would offset their demands and thus have minimal impact on prices. An increasing number of top financial journals now view research on investor sentiment as a complement to classical financial theory. Additionally, since the rise of behavioral finance theory by Nobel laureate Robert Shiller, more and more scholars have focused on financial anomalies that challenge the rational person hypothesis. The research paradigm of behavioral finance starts with financial anomalies to explore the causes of investor behavior, in order to explain one "mystery" after another. Ren and Wu (2020) took an innovative approach to capture and detect herd behavior using investor sentiment. This method, from both theoretical and empirical perspectives, proactively presented the psychological state of herd behavior before decision-making occurred, overcoming the lagging nature of using capital prices as a measure of behavioral outcomes from the perspective of measuring emotions. However, building upon Ren and Wu (2020)'s research, our study takes a further step by shifting the research perspective to explore social media sentiment rather than investor sentiment.

As investor sentiment represents the emotional views expressed by investors in stock forums regarding investment strategies, social media sentiment refers to the emotional state demonstrated by people in daily discussions about investment news and content. In our research, we expand the concept of investor sentiment and focus on social media sentiment as the main research object. The significance of this study lies in clarifying the concept of sentiment and distinguishing between investor sentiment and social media sentiment in identifying herd behavior.

Herd behavior is a crucial indicator of potential systemic risk (Dhaene et al., 2012), and it is important for governments and regulatory agencies to monitor this phenomenon in real-time. Our research indicates that the impact of social media information dissemination on emotional contagion can further spread to stock market investment behavior. Therefore, it is essential for regulatory agencies and listed companies to create a positive social media sentiment atmosphere. In addition, due to the technical challenges of extracting emotions from text content, we have improved the sentiment analysis models used in previous studies. Herd behavior is not only a financial phenomenon but also a topic of interest in psychology, sociology, and communication studies. We believe that it is important to not only analyze financial models for rational people but also pay attention to human cognition, which has significance implications for promoting interdisciplinary research.

Declaration of competing interest

No conflict of interest exits in the submission of this manuscript, and manuscript is approved by all authors for publication.

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