Mathematical Biosciences and Engineering

http://www.aimspress.com/journal/MBE

MBE, 20(5): 9305–9326.
DOI: 10.3934/mbe.2023408
Received: 11 January 2023
Revised: 02 March 2023
Accepted: 07 March 20233
Published: 16 March 2023

Research article

Impact of online public opinion regarding the Japanese nuclear wastewater incident on stock market based on the SOR model

Wei Hong[1,2,3,*], Yiting Gu[1], Linhai Wu[1,2,3] and Xujin Pu[1,2,3]

[1] School of Business, Jiangnan University, Wuxi, China
[2] Food Safety Research Base of Jiangsu Province, Jiangnan University, Wuxi, China
[3] Institute for Food Safety Risk Management, Wuxi, China

* **Correspondence:** Email: hongwei@jiangnan.edu.cn; Tel: +8618751568858.

Abstract: The exposure of the Japanese nuclear wastewater incident has shaped online public opinion and has also caused a certain impact on stocks in aquaculture and feed industries. In order to explore the impact of network public opinion caused by public emergencies on relevant stocks, this paper uses the stimulus organism response(SOR) model to construct a framework model of the impact path of network public opinion on the financial stock market, and it uses emotional analysis, LDA and grounded theory methods to conduct empirical analysis. The study draws a new conclusion about the impact of online public opinion on the performance of relevant stocks in the context of the nuclear waste water incident in Japan. The positive change of media sentiment will lead to the decline of stock returns and the increase of volatility. The positive change of public sentiment will lead to the decline of stock returns in the current period and the increase of stock returns in the lag period. At the same time, we have proved that media attention, public opinion theme and prospect theory value have certain influences on stock performance in the context of the Japanese nuclear wastewater incident. The conclusion shows that after the public emergency, the government and investors need to pay attention to the changes of network public opinion caused by the event, so as to avoid the possible stock market risks.

Keywords: emergency; online public opinion; prospect theory; stock market; SOR model

1. Introduction

Nuclear pollution has been a significant threat to the global environment. Some scholars point out that nuclear leakage can have acute health impacts on humans and chronic health impacts on various areas [1]. "On April 9, 2021, the Japanese government basically decided to discharge the nuclear sewage from the Fukushima Daiichi nuclear power plant into the sea," the Beijing Daily reported. The news immediately triggered a heated discussion among international and domestic netizens. The People's Daily reported that "scientific research institutions calculate that from the moment the nuclear wastewater is discharged into the sea, radioactive pollutants will spread to more than half of the Pacific within 57 days, and the United States and Canada will be affected by nuclear pollution in three years." People are concerned about seafood safety given the negative impact of nuclear wastewater discharged into the sea. The convenience of the Internet has promoted the outbreak of public opinion, resulting in an increasing number of investors paying attention to related stocks of aquaculture and feed industries, thereby leading to a sharp decline in the stock price of marine aquaculture and a rise in the stock price of freshwater aquaculture, which also had an impact on the stock performance of related feed industries [2].

The 48th statistical report on China's Internet Development shows that China had 1.011 billion internet users in the first half of 2021, and the Internet penetration rate reached a record high of 71.6%. With the continuous development and popularization of the Internet and mobile phones, more and more people acquire all kinds of information through convenient and low-cost network platforms, such as microblogs, TikTok, stock bar and so on, where they interact [3]. Compared with the traditional manner of obtaining information, people can obtain more information through the Internet. Concurrently, investors will use the platform to share their knowledge and opinions to Internet users and influence other investors. The dissemination of online public opinion has developed from relying on traditional professional media channels to the parallel dissemination of public media and We media. This open information exchange channel can impact the emotions, attitudes and behaviors of Internet users, thus eventually affecting the financial market. China's central economic conference in 2021 pointed out that "next year's economic work should put stability first and seek progress while maintaining stability." The 21st century pandemic has intensified the complexity, severity and uncertainty of the external environment. Thus, it is more necessary to adhere to the countermeasures pointed out in the meeting, and "we must adhere to the working tone of seeking progress while maintaining stability, adjust policies and promote reform in a timely manner and with appropriate efficiency. We must make progress first, then make breakthroughs, and proceed steadily to maintain overall social stability." Analyzing the impact of online public opinion on the performance of the stock market and exploring the governance strategies of online public opinion are crucial to stabilize the financial market.

Many scholars have studied the impact of media on the stock market. Media attention will significantly impact stock performance during an event. Some scholars believe that news or reports published by the media attract investors' attention, affect investors' cognition, promote investment decisions and thus affect stock price fluctuations, which can promote the improvement of stock returns [4–6]. However, some scholars believe that due to the risk of information asymmetry, stocks with low media attention must be compensated by a certain premium [7]. Moreover, many scholars have confirmed that the mood of the media will affect stock prices variedly. Most scholars believe that the pessimism of the media will cause downward pressure on the price, and negative reports may lead to the decline and violent fluctuation of the company's future stock price [8–10]. The positive media sentiment will fluctuate the stock price more gently, which may increase stock returns [9–12]. Overall, media reports and emotions impact stock performance.

Information acquisition and opinion exchange in the process of social interaction, as well as the dissemination of optimism or pessimism, significantly impact investors' financial decision making. Relevant studies show that public opinion sentiment is an important factor affecting the performance of the stock market. Some scholars use external indicators to measure investor sentiment and explore the impact of investor sentiment on stock market performance [13–17]. Some scholars also conducted emotional analysis through text mining and machine learning to explore the relationship between investor sentiment in online forums and the stock market [3,18,19]. Public opinion sentiment will impact the performance of the stock market. In addition to sentiment analysis, other scholars have studied the relationship between text content and stock [20–22]. Thus, the text of public opinion also impacts stock performance.

In addition, some scholars have studied the impact of risk appetite on the stock market on the basis of prospect theory. Barberis and Huang (2008) studied the utility of prospect theory obtained by investors from the value change of their portfolio and used prospect theory to predict the impact of the skewness of securities return distribution on securities prices [23]. Scholars also employed various techniques to measure the skewness and confirmed that more positive biased stocks will have lower average returns [24–26]. Prospect theory holds that people are risk averse when they gain and risk tolerant when they face loss. People react differently to loss and gain, and the pain brought by loss is far greater than the pleasure brought by gain. Some scholars have used prospect theory to construct prospect theory value and have proven that prospect theory value impacts stock returns [27–29].

Most studies explored the impact on the whole stock market and took the market index as the research object. However, few studies have analyzed the performance of relevant stocks for specific public opinion events. Most existing studies explored the impact of a specific factor on the stock market, such as the impact of media sentiment on the stock market. Few scholars have explored the impact of online public opinion on the stock market from a relatively comprehensive perspective of multiple factors. Concurrently, few scholars have explored the impact of the theme of public opinion on stock performance. In addition, most scholars used economic indicators and machine learning methods to measure sentiment. The research results show that the data of machine learning can measure sentiment more effectively. The SOR theory is a theoretical model of consumer behavior proposed by environmental psychologists Mehrabian and Russell based on the stimulus-response theory of Watson, the founder of behaviorist psychology. Public opinion caused by emergencies and prospect theory stimulate investors to make decisions and eventually lead to changes in stock performance, which is highly consistent with the SOR framework. Thus, we used machine learning to measure sentiment based on SOR model and employed the LDA topic analysis method to explore whether online public opinion will have a certain impact on the stocks of the industry related to the event in the context of public emergencies.

The findings of this paper are highly significant to the management of online public opinion in emergencies. Promoting the rational management of online public opinion can improve market efficiency and promote the steady operation of the financial market. This research can also help investors analyze the possible impact of online public opinion on relevant stocks in the face of emergencies and make or change timely investment strategies to reduce losses.

The rest of the article is organized as follows. Section 2 presents the research hypotheses. Section 3 discusses the data used and defines the key variables for the analysis. Section 4 presents the main research results. Section 5 summarizes and puts forward suggestions.

2. Research hypothesis

On the basis of the previous research results, we use the SOR model to study the impact of online public opinion on related stocks. This chapter introduces the SOR model and states the reasons for choosing the model. The assumptions are put forward through literature review.

The SOR model is a general model of human behavior. It improves the traditional S-R model and holds that the connection between stimulus and response is not direct and mechanical, but they are connected through the internal state of the organism as an intermediary link. When facing various internal and external stimulation, the subject will actively and selectively obtain stimulation for processing, form cognitive structure and finally respond. This process is represented by the formula "S-O-R," i.e., stimulation-individual physiological and psychological-response. Many scholars have used SOR framework to construct theoretical models in related fields. For example, Yang (2021) proposed a theoretical model of health anxiety on the basis of the SOR framework in which metacognitive beliefs and catastrophic misunderstandings are the intermediary between stimulants and health anxiety [30]. Tang (2019) used the SOR theory to explore the impact of environmental stimuli and internal psychological state on employees' willingness to save energy [31]. After the occurrence of emergencies, the external information and interaction of media and public opinion stimulate the cognitive changes of investors, coupled with the joint action of investors' internal prospect theory, promote investors to make decisions and finally lead to stock performance changes. This process is highly consistent with the SOR theory framework. Therefore, this paper took the online media reports and the interaction on the network message board as the external stimulus and the loss aversion as the internal stimulus. The two work together to lead to the change of investors' cognitive structure and finally making investment decisions, which will impact the stock market. Under the SOR model framework, this paper constructed a framework model of the impact path of network public opinion on the financial stock market to explore the impact of online public opinion caused by public emergencies on the stock market combined with prospect theory. The research framework of this paper is shown in Figure 1.

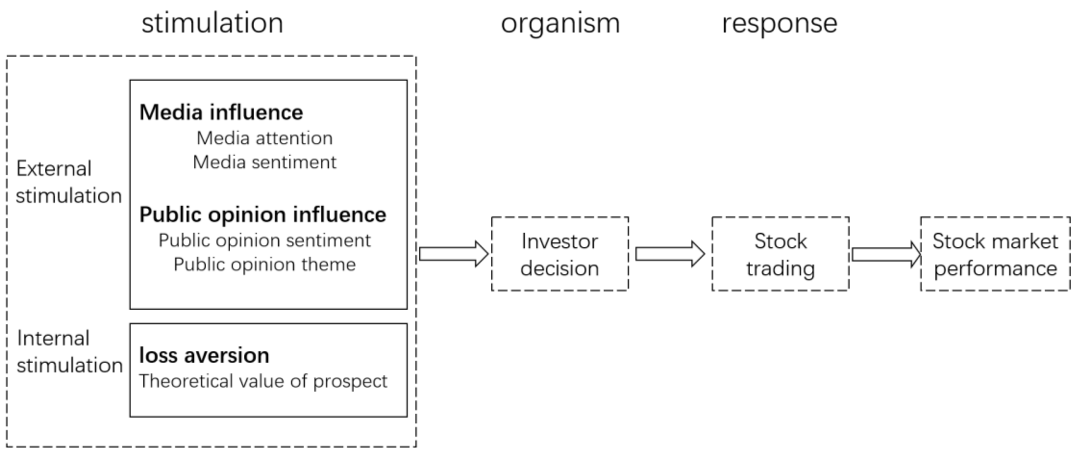

Figure 1. Research framework.

In real life, various Internet media platforms have become an important channel for the public to obtain timely information. The impact of media attention refers to the impact of media news release on investors without considering the impact of information effect. Existing research shows that media attention significantly impact the stock performance in the event. Some studies show that positive or neutral media reports on companies have a positive impact on the company's stock price. For example, Huberman and Regev (2001) found that news about a company's new drugs published by the New York Times that had appeared in other newspapers and magazines attracted public attention, and the company's share price soared that day. The renewed coverage of the news grabbed investors' attention, causing stock returns to keep rising [4]. Bushee et al. (2010) pointed out that more published reports can reduce the degree of information asymmetry and escalate stock price and trading volume [32]. Da et al. (2011) took Google search index as a proxy indicator of media attention and found that the stock price of stocks with high search volume will rise within two weeks and reverse within one year [33]. Comiran et al. (2017) found that the number of news media before release was positively correlated with the quotation discount of SEOs, and the amount of news reports was negatively correlated with the cumulative abnormal return rate in the three days before and after SEOs [34]. In terms of the impact of negative news reports on stock prices, Chan (2003) divided news into positive news and negative news. It was found that if the media reported a listed company mostly in a positive way, the stock price of the listed company would reverse in the medium and long term; and while the news media reported a listed company mostly in a negative way, the stock price of the company will have a strong price drift in the medium and long term [35]. Tetlock et al. (2008) used linguistic analysis to classify newspaper reports on listed companies into positive reports and negative reports. They found that negative reports would exert downward pressure on initial stock prices of listed companies, but after a period of time, stock prices would reverse [36]. Media attention also has a certain impact on stock volatility. Heerde et al. (2015) showed that media reports will attract the public's attention, and the information of the reported company will also be reflected in the stock market, which will affect the cognition of investors and promote investment decisions, thus affecting the fluctuation of stock price [6]. Jiao et al. (2020) uncovered that media reports have a certain impact on stock volatility and turnover. Traditional news media reports predict the subsequent decline of stock volatility and trading volume, but social media reports predict the increase of volatility and trading volume [37]. Most of the above articles are about the impact of media attention on specific company events on the stock price of the company. There is a lack of research on the impact of media attention on event-related stocks under public emergencies. With the exposure of the Japanese nuclear wastewater incident, the media continued to make relevant reports to attract investors' attention, which led to reduction of relevant stock returns and the increase of volatility. Referring to the previous conclusions, this paper believes that media attention impacts relevant stock performance under public emergencies. Thus, the first hypothesis is proposed.

Hypothesis 1a：*Media attention has negative impact on stock returns.*

Hypothesis 1b：*Media attention has positive impact on stock volatility.*

Concurrently, many scholars have proven that optimistic (pessimistic) media sentiment has a positive (negative) impact on stock prices, and optimistic (pessimistic) media sentiment has a negative (positive) impact on stock volatility. For example, Tetlock (2007) qualitatively measured pessimistic news reports, indicating that a high degree of media pessimism indicates downward pressure on the price [8]. Engelberg (2008) found that positive reports may indicate that the company will develop positively, and its share price will rise, whereas negative reports may indicate that the company's share price will decline in the future [9]. On this basis, relevant scholars have further investigated the impact of media sentiment on stock performance. Uhl (2011) believes that fundamental and behavioral factors will affect asset prices. Using two novel sentiment data sets, the author demonstrates that fundamental macro factors and media sentiment are significantly positively correlated with stock returns. The vector error correction model shows that media sentiment causes the continuous rise of stock returns (monthly) and that asset prices overreact to media sentiment [11]. Suleman (2012) studied the impact of political news on the KSE100 index and found that positive political news can increase the index return and reduce the fluctuation. Contrarily, negative political news will reduce the index return and increase the fluctuation [12]. Huang and Zhang (2021) used machine learning technology to construct the index of industry-level media tone, discussed its cross-sectional relationship with China’s stock return and found that the stocks of industries with a positive media tone received much higher future returns than those with a negative media tone, and the return premium of industry-level media with a higher tone lasted for two months [38]. He et al. (2022) constructed the investor sentiment index through the text analysis of China’s major financial newspapers, used Word2Vec technology and dictionary method to measure the text tone in media news, explored its relationship with China’s A-share stocks and uncovered that the media sentiment was positively (negatively) correlated with the cross section of stock returns in the short-term (long-term) range [39]. Wang et al. (2022) found that positive change of mood can lead to upward correction of volatility [40]. Du et al. (2022) divided Chinese media sentiment into positive, neutral and negative emotions, and they found that companies without positive or negative news have significant positive returns, and negative news has the most significant impact on stock prices [10]. Most of the existing literature has explored the impact of industry media sentiment on the performance of stock indexes, while few scholars have explored the impact of media sentiment on the performance of event-related stocks in the context of public emergencies. Because of the negative impact of the nuclear wastewater event, the mood keynote of the media should be negative. The more negative the mood, that is, the smaller the media mood value, will lead to lower stock returns and volatility. Thus, this paper puts forward the second hypothesis.

Hypothesis 2a：*Media sentiment has positive impact on stock returns.*

Hypothesis 2b：*Media sentiment has positive impact on stock volatility.*

People’s information acquisition and opinion exchange in the process of social interaction, as well as the dissemination of optimism or pessimism, significantly impact investors’ financial decision making. The relevant research shows that public opinion sentiment is an important factor affecting the performance of the stock market. The measurement of public opinion sentiment is basically divided into two categories. One is to measure public opinion sentiment by using indicators, such as financial market index and economic index. For example, Wurgler and Baker (2006) used the discount rate of closed-end funds to measure investor sentiment. Fisher and Statman (2003) employed the consumer confidence index as the proxy variable [14]. Cohen et al. (2009) considered the impact of stock trading volume on the basis of a single variable and used the principal component analysis method to construct the investor sentiment index [41]. The other is to make an emotional analysis through text mining and machine learning. For example, Renault (2017) conducted an emotional analysis on the news of the stock evaluation community. Using the online investor sentiment 30 minutes after the opening, it successfully predicted the return of the S&P 500 stock index 30 minutes before the closing and it is believed that this predictive power came from novice traders [18]. Da et al. (2015) constructed the fears index as a proxy variable of investor sentiment with substantial online data and the amount of family search for words, such as “recession” and “unemployment.” The study found that it can predict the reversal of short-term yield and the temporary increase of volatility [42]. Bartov et al. (2018) classified the positive and negative emotional polarity of opinions expressed by individual accounts on Twitter. After controlling other factors that determine earnings, they found that Twitter's comprehensive opinions can help predict quarterly earnings and abnormal returns before and after earnings announcements [19]. Yang et al. (2017) found a significant positive correlation between investor sentiment and stock returns by analyzing the unique stock trading data set of the Korean stock market [43]. Li et al. (2021) selected the sentiment proxy from the transaction data of China's A-share market, Hong Kong stock market and the US market and took the index synthesized by principal component analysis as the comprehensive index of international investor sentiment of China's stock market. The results show that international investor sentiment has a significant predictive power for the future returns of the Chinese stock market [44]. Lv et al. (2022) used the text analysis method to construct positive and negative investor sentiment indicators and found that there is a causal relationship between sentiment indicators and stock returns [3]. Kim and Lee (2022) examined the relationship between investor sentiment and stock returns in two different Korean stock markets and unveiled that investor sentiment significantly impacts stock returns [17]. Few existing studies focus on the impact of public opinion caused by a public emergency on the performance of event-related stocks. The continuous media coverage of the nuclear wastewater event has led to investors' continuous attention to the event, and their pessimism about the event has a significant impact on stock decision-making. Thus, we discussed the impact of public opinion on the performance of stock market under the public event of nuclear wastewater. Therefore, the third hypothesis is proposed.

Hypothesis 3a：*Public opinion sentiment has positive impact on stock returns.*

Hypothesis 3b：*Public opinion sentiment has positive impact on stock volatility.*

The relationship between news text or online message board text and stocks has been extensively studied. For example, Ammann et al. (2014) revealed that a certain correlation exists between German financial news and the return of the German stock market by constructing a word frequency index [45]. Wong et al. (2014) used the sparse matrix decomposition algorithm. The results show that a correlation exists between the data of Twitter short article and the closing price of S&P 500, and the closing price can be predicted according to the Twitter text [46]. Shynkevich et al. (2015) used the text of financial news to predict the change of stock price by using the multi-core SVM model [20]. Yun (2019) used the titles of Korean news articles and word embedding to extract features. The features are transmitted to the CNN model to predict the stock price five days after the trading day, with an accuracy rate of 53% [21]. Zhang et al. (2022) introduced a novel knowledge-driven approach for long-term stock movement prediction based on Chinese research reports and proposed the Multi-module Feature Fusion method based on the pre-trained language model FinBERT, which can effectively fuse textual features from research reports [22]. The above scholars have demonstrated the relationship between text structure or characteristics and stock performance. Few scholars used the LDA topic model to investigate the relationship between topics and stocks. Since David Blei proposed the classical LDA Algorithm of topic model in 2003, this method has been widely used in text mining and other fields and has good generalization ability. Therefore, this paper used the LDA topic method to explore whether public opinion topics impact stocks and puts forward the fourth hypothesis.

Hypothesis 4a：*The theme of public opinion impacts stock returns.*

Hypothesis 4b：*The theme of public opinion impacts stock volatility.*

Barberis (2013) pointed out that prospect theory can help explain the overall return of the stock market, analyzed the difference of cross-sectional return of assets and explained the trading behavior of financial assets [47]. Prospect theory is one of the important research results of behavioral finance. It was proposed by Professor Kahneman and Professor Tversky in 1979 and applied psychological research to economics [48]. On the premise of bounded rationality, prospect theory holds that investors will not be completely rational in the face of uncertain situations, but their risk preference is affected by early profits or losses according to their subjective evaluation of profits and losses and perceived value. Its value curve shows an asymmetric S-shape (as shown in Figure 2), indicating that people are risk averse when they gain and risk preference when they face loss. People react distinctly to loss and gain, and the pain brought by loss is far greater than the happiness brought by gain. Barberis and Huang (2008) used prospect theory and found that the skewness of securities return distribution will impact securities prices. When the right tail of a stock's return distribution is wider than its left tail, the stock will become particularly popular, which will increase the stock price and eventually lead to a lower average return for investors [23]. Scholars have also used various techniques to measure skewness and confirmed the above basic assumption that more positive biased stocks will have lower average returns [24–26]. Barberis et al. (2016) used prospect theory to construct prospect theory value and confirmed that prospect theory value impacts stock returns [27]. Wang et al. (2021) and Junior et al. (2021) have proved empirically that the prospect theory value has a strong prediction ability for stock returns, and the probability weighting function is the key factor [28,29]. We assume that investors evaluate risk under the framework of prospect theory and take the prospect theory value corresponding to the distribution of stock historical return as one of the basis of investment decision making. Stocks with high prospect theory value are more attractive to investors. Therefore, stocks with high prospect theory value will attract investors to overbuying behavior, and the volatility will increase. The stock price will be overvalued due to investors' buying behavior, and the expected yield will decline. Thus, the fifth hypothesis is proposed.

Hypothesis 5a：*Prospect theory value has negative impact on stock returns.*

Hypothesis 5b：*Prospect theory value has positive impact on stock volatility.*

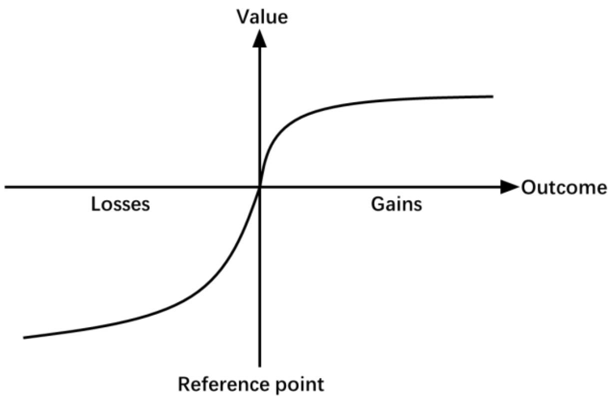

Figure 2. Prospect theory value function. Reference source：Kahneman, D. & Tversky, A. (1979).

3. Research design

This chapter discusses the samples and data sources selected in this paper on the basis of the previous assumptions, and it proposes the calculation method of variables and the research model of this paper. Figure 3 shows the research process and method of this article. LDA topic model analysis and grounded theory were used to work with data. The distributed lag model was used for empirical analysis.

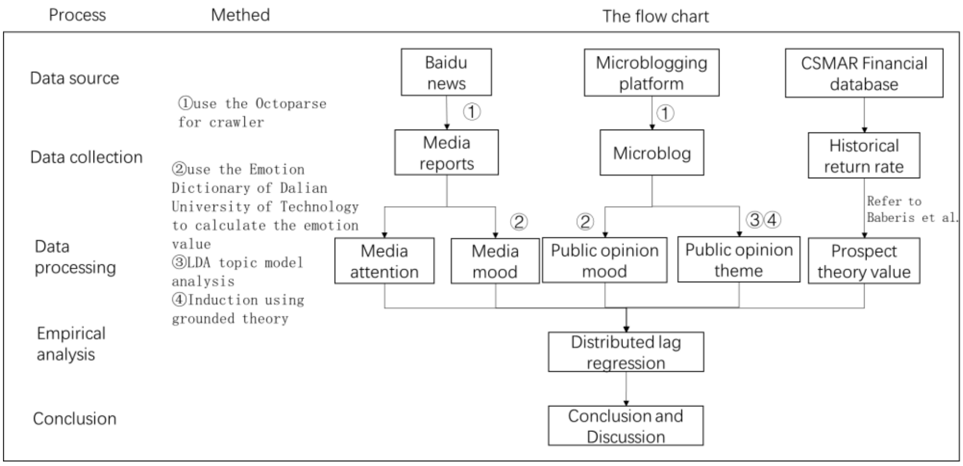

Figure 3. Research process and method.

3.1. Sample selection and data source

Referring to the Baidu Index provided by the Baidu search engine, Japanese nuclear wastewater keyword search index basically stabilized by early June 2021. The sample time span selected in this paper is 50 days after the exposure of the nuclear wastewater event, that is, from April 9, 2021, to June 17, 2021. As the most concerned part of Japanese nuclear wastewater incident is its impact on the ocean, the stocks of marine aquaculture, freshwater aquaculture and related feed industries have been greatly affected. Eastmoney is a well-known financial information website in China. Its concept stocks of aquaculture and feed cover most of the Chinese stocks related to the event, including most stocks in marine aquaculture, freshwater aquaculture and related feed industries. Thus, 18 stocks in the aquaculture and feed concept stocks of Eastmoney.com were selected as the observation object to explore the impact of Japanese nuclear wastewater incident on China's event-related stocks. CSMAR database is a professional economic and financial data platform. At present, it is one of the most comprehensive economic and financial research databases. The financial data required in this paper are from the CSMAR database. In the regression model, the fixed effects of stock and year were controlled. Python was used for related operations.

3.2. Return and volatility

In this paper, the daily rate of return, highest price and lowest price data of 18 stocks in aquaculture and feed concept stocks from April 9, 2021, to June 17, 2021, were obtained through the CSMAR financial database. A total of 736 sample observations were obtained from 16 stocks with complete data. The daily rate of return was selected to represent the stock return. With reference to Li et al. (2021), the historical volatility of the past five days is used to represent the single day stock volatility. The calculation formula is

$$\text{Volatility}_{i,t} = \sqrt{\frac{1}{n-1}\sum_{t-n+1}^{t} r_{i,t}^{2}} \tag{1}$$

where $r_{i,t}$ is the return rate of stock i on day t, n = 5, representing the historical volatility calculated using the trading data of the past five days.

3.3. Measurement of online public opinion variables

In this study, whether network public opinion and psychological factors will affect the performance of relevant stocks after emergencies is mainly investigated. Media attention, media emotion, public opinion emotion, public opinion theme and prospect theory value are the main explanatory variables of this paper.

3.3.1. Media attention and media emotion

To solve the problem of high cost and slow speed of manual data collection, Octoparse was used to collect data. The collector must only formulate the collection process on the basis of the required data and use various elements to compile the collection rules in the process designer. The Octoparse will enter the website to be collected according to the established rules and collect the data of the required dates and keywords. The news reports released by the media in Baidu news were crawled through Octoparse, taking Japanese nuclear wastewater as the keyword, and the number of news reports released every day was taken as a measure of media attention. The method of unsupervised machine learning was used to measure the emotion. The crawled news report content was used as the data, and the emotion value of daily news report was calculated as the measurement index of media emotion through the vocabulary and corresponding emotion intensity defined by the DLUTEO emotional Dictionary of Dalian University of technology.

3.3.2. Public opinion emotion and public opinion theme

The microblog with Japanese nuclear wastewater as the keyword was crawled through Octoparse. Taking the crawling microblog content as the data of this paper, the emotion value of daily microblog was calculated through the DLUTEO, the emotion Dictionary of Dalian University of technology, as the measurement index of public opinion emotion.

Drawing on previous studies, the following methods are used to measure the theme of public opinion: first, the crawled microblog text is segmented by the self-contained Dictionary of Python's open source "Jieba" Chinese word segmentation module and the names and proper nouns involved in the event. Second, on the basis of the calculation results of confusion degree, multiple subject words of daily microblog text are obtained by using LDA topic model. Third, on the basis of the process of grounded theory, open coding, spindle coding and selective coding are carried out to obtain multiple core themes in the event period. Open coding is shown in Table 1. The key information extracted from each topic every day was named and conceptualized, and 170 open codes are finally obtained. The spindle codes and selective codes are exhibited in Table 2. The open codes were organically integrated and connected to obtain 24 spindle codes. By analyzing the conceptual category and internal relationship of spindle codes, five core codes with strong correlation ability were determined, including Chinese attitude, public attitude, impact outlook, international relations and developments. Table 2 shows some of the core codes. Finally, the numbers 1–5 are used to indicate the theme attribution of microblog published daily. For example, if the theme of April 9, 2021, is 3, the theme of public opinion on that day belongs to impact outlook.

Table 1. Open coding of public opinion theme.

Theme keywords	Open coding
Impact, fishing, nuclear contamination, agency, radioactive material, study, human, sewage, time, nuclear power plant, equipment, storage, power company, calculation results, construction	Impact on fisheries
Effect, human, wastewater, discharge into the sea, nuclear power plant, seafood, radioactive substances, study, nation, hazard, institutions, calculation results, regional, nuclear contamination, radioactivity	Effects of radioactive substances on nuclear wastewater
Discharge into the sea, seafood, plan, cost, sea water, nation, method, the whole world, wastewater, nuclear pollution, global, earth, nuclear power plant, all mankind, earthquake	Impact on seafood
Netizen, news, nuclear power plant, Japanese, officials, power company, finance, minister, water storage, post, reason, spend money, cheat, sewer, international	Statement by the Deputy Prime Minister of Japan

Table 2. Spindle coding and core coding of public opinion theme.

Spindle coding	Core coding
Discharge into the sea, news, girl, net friend, child, mother, protect the environment, daughter, picture, sewer, conscience (the girl in grade one of junior middle school cried bitterly for discharging nuclear wastewater into the sea) Analysis, professional, feeling, crossover, scholar, principle, article, flying snow, thumb, engineer, suggestion, thing, proof (praise for the nuclear engineer published popular science article) Japanese, netizen, sewage, surfing, international, guy, global, redraw, nuclear pollution, discharge into the sea, detection, observer, hazard, plan, people, nuclear accident, biological, wave, malformation, standard, essence, painter, detail, works (a young artist painted radio-world painting to criticize Japan for discharging nuclear wastewater) Nuclear accident, public relations, RMB, experiment on one's own, discharge into the sea, funds, harm, politicians, nuclear pollution, publicity, impact, about, national, Revelations, a huge sum of money (anger over Japan's expensive PR for not dealing with nuclear waste)	Public attitudes

3.3.3. Prospect theory value

Referring to the calculation method of Baberis et al. (2016), it is assumed that investors calculate their prospect theory value according to the historical distribution of monthly stock returns. For stock i, obtain the historical rate of return data from month t-1 to month t-60 and the corresponding risk-free rate of return, calculate the risk-free adjusted rate of return for the 60 months, and arrange them in ascending order. Assuming that m rates of return are negative and the remaining n rates of return are positive, where n = 60-m, the historical distribution of excess rate of return of stock i can be expressed in the following form:

$$\left(r_{-m},\frac{1}{60};r_{-m+1},\frac{1}{60};\dots;r_{-1},\frac{1}{60};r_{1},\frac{1}{60};\dots;r_{n-1},\frac{1}{60};r_{n},\frac{1}{60}\right) \tag{2}$$

where the m risk-free adjusted returns corresponding to r_{-m}... r_{-1} are negative, and the n risk-free adjusted returns corresponding to r_1... r_n are positive. Then the prospect theory value of stock i in month t is

$$PT_{i,t}=\sum_{i=-m}^{-1}v(r_i)\left[\omega^-\left(\frac{i+m+1}{60}\right)-\omega^-\left(\frac{i+m}{60}\right)\right]+\sum_{i=1}^{n}v(r_i)\left[\omega^+\left(\frac{n-i+1}{60}\right)-\omega^+\left(\frac{n-i}{60}\right)\right] \tag{3}$$

The forms of value function and probability weight function are as follows:

$$\mathrm{v}(x)=\begin{cases}x^{\alpha},x>0\\-\lambda(-x)^{\alpha},x<0\end{cases} \tag{4}$$

$$\pi_i=\begin{cases}\omega^+(p_i+\dots+p_n)-\omega^+(p_{i+1}+\dots+p_n),0\le i\le n\\\omega^-(p_{-m}+\dots+p_i)-\omega^-(p_{-m}+\dots+p_{i-1}),-m\le i\le 0\end{cases} \tag{5}$$

$$\omega^+(P)=\frac{P^{\gamma}}{(P^{\gamma}+(1-P)^{\gamma})^{\frac{1}{\gamma}}},\omega^-(P)=\frac{P^{\delta}}{(P^{\delta}+(1-P)^{\delta})^{\frac{1}{\delta}}} \tag{6}$$

The specific parameter setting in the prospect theory formula uses the calibration results of Tversky and Kahneman (1992), i.e., $\alpha = 0.88$，$\lambda = 2.25$, $\gamma = 0.61$, $\delta = 0.69$.

The monthly returns of 16 stock samples were obtained from the CSMAR database from April 2016 to May 2021, and the prospect theory value in April, May and June 2021 was calculated on the basis of the above method.

3.4. Model establishment

To empirically test the hypothesis and characterize the lag phenomenon from the occurrence of online public opinion to the reaction of the market, a distributed lag model is constructed on the basis of the research methods of Chen et al. (2013) to test the impact of online public opinion and prospect theory value on stock performance, and its expression is given by Eq (7) [49]. The distributed lag model contains not only the current values of explanatory variables but also their lag values.

$$\begin{cases}Return_t=\beta_0+\sum_{i=0}^{m}\alpha_iMA_{t-i}+\sum_{i=0}^{m}\beta_iMM_{t-i}+\sum_{i=0}^{m}\gamma_iPM_{t-i}\\\qquad+\sum_{i=0}^{m}\sum_{n=1}^{5}\delta_iPT_{n,t-i}+\sum_{i=0}^{m}\mu_iPR_{t-i}+X+\varepsilon_t\\Volatility_t=\beta_0+\sum_{i=0}^{m}\alpha_iMA_{t-i}+\sum_{i=0}^{m}\beta_iMM_{t-i}+\sum_{i=0}^{m}\gamma_iPM_{t-i}\\\qquad+\sum_{i=0}^{m}\sum_{n=1}^{5}\delta_iPT_{n,t-i}+\sum_{i=0}^{m}\mu_iPR_{t-i}+X+\varepsilon_t\end{cases} \tag{7}$$

The explanatory variables in the model are the daily return and volatility of stock, where MA_{t-i} is the media attention, MM_{t-i} is the media sentiment, PM_{t-i} is the public opinion sentiment, PT_{t-i} is the public opinion theme, PR_{t-i} is the prospect theory value, and X is a group of control variables. Its setting refers to the common variables in existing research and real transactions, including the Cumulative returns and average volatility over the previous 10 trading days, turnover rate, P/E ratio, P/B ratio, P/S ratio and trading volume, and ε_t is the random error term. Like Antweiler and Frank (2004), we believe that only the most recent online public opinion will impact the return and trading volume, so the maximum lag set in the model is 2. Moreover, as the data in this paper are panel data, to control the impact of stocks and years, the two-way fixed effect model was used. In the regression, three models were used for stepwise regression. The formula for Models (1)–(3) is shown in Eqs (8)–(10).

$$\begin{cases} Return_t = \beta_0 + \alpha_0 MA_t + \beta_0 MM_t + \gamma_0 PM_t \\ \qquad + \sum_{n=1}^{5} \delta_0 PT_{n,t} + \mu_0 PR_t + X + \varepsilon_t \\ Volatility_t = \beta_0 + \alpha_0 MA_t + \beta_0 MM_t + \gamma_0 PM_t \\ \qquad + \sum_{n=1}^{5} \delta_0 PT_{n,t} + \mu_0 PR_t + X + \varepsilon_t \end{cases} \tag{8}$$

$$\begin{cases} Return_t = \beta_0 + \sum_{i=0}^{1} \alpha_i MA_{t-i} + \sum_{i=0}^{1} \beta_i MM_{t-i} + \sum_{i=0}^{1} \gamma_i PM_{t-i} \\ \qquad + \sum_{i=0}^{1} \sum_{n=1}^{5} \delta_i PT_{n,t-i} + \sum_{i=0}^{1} \mu_i PR_{t-i} + X + \varepsilon_t \\ Volatility_t = \beta_0 + \sum_{i=0}^{1} \alpha_i MA_{t-i} + \sum_{i=0}^{1} \beta_i MM_{t-i} + \sum_{i=0}^{1} \gamma_i PM_{t-i} \\ \qquad + \sum_{i=0}^{1} \sum_{n=1}^{5} \delta_i PT_{n,t-i} + \sum_{i=0}^{1} \mu_i PR_{t-i} + X + \varepsilon_t \end{cases} \tag{9}$$

$$\begin{cases} Return_t = \beta_0 + \sum_{i=0}^{2} \alpha_i MA_{t-i} + \sum_{i=0}^{2} \beta_i MM_{t-i} + \sum_{i=0}^{2} \gamma_i PM_{t-i} \\ \qquad + \sum_{i=0}^{2} \sum_{n=1}^{5} \delta_i PT_{n,t-i} + \sum_{i=0}^{2} \mu_i PR_{t-i} + X + \varepsilon_t \\ Volatility_t = \beta_0 + \sum_{i=0}^{2} \alpha_i MA_{t-i} + \sum_{i=0}^{2} \beta_i MM_{t-i} + \sum_{i=0}^{2} \gamma_i PM_{t-i} \\ \qquad + \sum_{i=0}^{2} \sum_{n=1}^{5} \delta_i PT_{n,t-i} + \sum_{i=0}^{2} \mu_i PR_{t-i} + X + \varepsilon_t \end{cases} \tag{10}$$

4. Empirical analysis and results

4.1. Descriptive statistics

The Z-score model is adopted for standardized data processing, and the transformation model is as follows:

$$Z = \frac{X - \bar{X}}{\sigma} \tag{11}$$

$\bar{X}$ is the mean value of variable X, and σ is the standard deviation of variable X. The processed data conform to the standard normal distribution with mean of 0 and standard deviation of 1. Table 3 lists the descriptive statistics of the main variables after standardization.

To prevent pseudo regression, the stability of the panel data must be verified. In this paper, Stata was used to conduct ADF unit root test, and the test results are shown in Table 4. The table shows that the P-values of return rate, volatility, media sentiment, media attention, public opinion sentiment and public opinion theme unit root test are all less than 1%, that is, the null hypothesis is rejected at the significance level of 1%, and panel data is a stable process. The p-value of the unit root test of the prospect theory value is 0.2, which is a non-stationary sequence. Therefore, first-order difference is carried out for all panel data. Table 4 shows that panel data after the first-order difference passes the ADF test, denoised as DReturn, DVolatility, DMM, DMA, DPM, DPT and DPR.

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
return	736	0	1	−3.661	5.909
volatility	736	0	1	−1.43	5.791
PR	736	0	1	−1.967	2.196
PM	736	0	1	−2.959	4.757
MM	736	0	1	−6.185	2.11
MA	736	0	1	−0.376	5.133

Table 4. Unit root test results.

	Return	Volatility	MM	MA	PM	PT	PR
Before difference	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.2010
After difference	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*

4.2. Online public opinion and stock yield

In this article, the bidirectional fixed effects model was used for regression. In addition, through autocorrelation test, heteroscedasticity and cross-sectional correlation test, it is believed that panel data have autocorrelation, heteroscedasticity and cross-sectional correlation. Therefore, GLS regression was used to remove the effects of autocorrelation, heteroscedasticity and so on. The regression results are shown in Table 5. In Table 5, explanatory variables and lag terms are gradually added into Models (1)–(3) to observe their impacts on the return rate.

Based on the return rate regression results in Table 5, we believe that the positive change of media attention will attract the attention of investors, leading to the decrease of stock returns in the future. Thus, Hypothesis 1a is verified, which is in line with the research result of Comiran F (2017). In the context of negative events, the increase of media attention will aggravate the negative impression of investors on relevant stocks, leading to the reduction of stock returns. The positive change of media sentiment in the current period will lead to the decline of current and future return rates, thus negating Hypothesis 2a. However, existing studies based on media sentiment, such as Engelberg (2008), Matthias (2011) and Suleman (2012), revealed that positive media sentiment positively impacts the yield, and negative reports may lead to the decline of the company’s stock price in the future. The research results of this article are different from theirs, which may be because the positive change of media sentiment cannot reverse the decline of stock prices in the context of major negative events. This article demonstrates that the positive change of public sentiment in the current period will lead to the increase of the future return rates, which is in line with the research results of Eli et al. (2018) and Yang et al. (2017). The positive public sentiment will lead to the increase of the return rates, which may be because the positive change of public sentiment in the current period must be reflected in the cognition of investors for 1–2 days, which leads to the lag response of yield growth, thus verifying

Hypothesis 3a. From the regression results of the theme change. The emergence of the theme of Chinese attitude will lead to the improvement of the current and future yield, the emergence of the theme of public attitude, impact outlook and international relations will lead to the improvement of the future yield. The emergence of the theme of development has no impact on the relevant stock yield, which verifies hypothesis 4a. The prospect theory believes that the high prospect theory value can attract investors to buy, which leads to the overvaluation of stocks. Therefore, the increase of the current prospect theory value will lead to the decline of the current yield, thus verifying Hypothesis 5a.

Table 5. Regression results of influencing factors of return rate.

	(1)	(2)	(3)
DMA_t	0.2173***	0.2481***	0.0731
DMA_{t-1}		-0.2351***	-0.2174***
DMA_{t-2}			-0.3135***
DMM_t	-0.0360	-0.0661*	-0.1564***
DMM_{t-1}		0.0014	0.0005
DMM_{t-2}			-0.0614**
DPM_t	-0.1538***	-0.1130***	0.0552
DPM_{t-1}		0.1047***	0.1777***
DPM_{t-2}			0.0473
$DPT1_t$	0.3650***	0.3132***	0.4274***
$DPT1_{t-1}$		0.3618***	0.6010***
$DPT1_{t-2}$			-0.2046
$DPT2_t$	0.0588	0.0728	0.2989
$DPT2_{t-1}$		-0.1273	0.4138**
$DPT2_{t-2}$			0.2766
$DPT3_t$	-0.0998	-0.02730	0.0003
$DPT3_{t-1}$		0.0634	0.3998***
$DPT3_{t-2}$			-0.1436
$DPT4_t$	0.0130	0.0235	-0.0093
$DPT4_{t-1}$		0.2553**	0.5855***
$DPT4_{t-2}$			-0.0923
$DPT5_t$	0	0	0
$DPT5_{t-1}$		0	0
$DPT5_{t-2}$			0
DPR_t	-0.6333*	-0.6845**	-0.5916**
DPR_{t-1}		0.2001	0.1138
DPR_{t-2}			0.1916
Control variable	Control	Control	Control
Stock	Control	Control	Control
Year	Control	Control	Control
Wald chi2	142.36	310.56	437.34
P	0.0000	0.0000	0.0000

4.3. *Online public opinion and stock volatility*

Like the return rate, GLS regression was used for volatility to remove the effects of autocorrelation and heteroscedasticity. The regression results are shown in Table 6. In Table 6, explanatory variables and lag terms are gradually added to Models (1)–(3) to observe their impacts on volatility.

Table 6. Regression results of influencing factors of volatility.

	(1)	(2)	(3)
DMA_t	0.2447***	0.2064***	0.2066***
DMA_{t-1}		-0.0362	-0.0377
DMA_{t-2}			-0.1029
DMM_t	0.0796***	0.0372	0.0095
DMM_{t-1}		-0.0287	0.0228
DMM_{t-2}			-0.0146
DPM_t	0.1340***	0.1499***	0.1581***
DPM_{t-1}		-0.1380***	-0.1604***
DPM_{t-2}			-0.0408*
$DPT1_t$	-0.0025	0.0985	-0.0909
$DPT1_{t-1}$		0.3684***	0.1819***
$DPT1_{t-2}$			-0.3735***
$DPT2_t$	-0.0974	0.0668	0.1370
$DPT2_{t-1}$		0.3309***	0.6165***
$DPT2_{t-2}$			-0.1375
$DPT3_t$	-0.0337	-0.0393	-0.2384***
$DPT3_{t-1}$		-0.0558	0.0751
$DPT3_{t-2}$			-0.4851***
$DPT4_t$	-0.0361	-0.1021	-0.2750***
$DPT4_{t-1}$		0.1467*	0.2721***
$DPT4_{t-2}$			-0.3319***
$DPT5_t$	0	0	0
$DPT5_{t-1}$		0	0
$DPT5_{t-2}$			0
DPR_t	1.3028***	1.1558***	0.9963***
DPR_{t-1}		0.3283	0.2930
DPR_{t-2}			-0.0363
Control variable	Control	Control	Control
Stock	Control	Control	Control
Year	Control	Control	Control
Wald chi2	164.46		322.94
P	0.0000	0.0000	0.0000

Table 7. Regression results after replacing variable calculation method.

	Logarithmic return rate	Historical volatility
DMA_t	0.0768	0.2280***
DMA_{t-1}	-0.2135***	-0.0485*
DMA_{t-2}	-0.3686***	-0.1096**
DMM_t	-0.1609***	0.0141
DMM_{t-1}	0.0041	0.0323*
DMM_{t-2}	-0.0685***	0.0389***
DPM_t	0.0645	0.1746***
DPM_{t-1}	0.1919***	-0.1224***
DPM_{t-2}	0.0521	0.0040
$DPT1_t$	0.4324***	-0.0497
$DPT1_{t-1}$	0.5998***	0.4461***
$DPT1_{t-2}$	-0.1946	-0.5499***
$DPT2_t$	0.3148	-0.1023
$DPT2_{t-1}$	0.4595**	0.5385***
$DPT2_{t-2}$	0.3109*	-0.3944***
$DPT3_t$	0.0071	-0.3243***
$DPT3_{t-1}$	0.4416***	0.2260***
$DPT3_{t-2}$	-0.1313	-0.6572***
$DPT4_t$	-0.0133	-0.2403***
$DPT4_{t-1}$	0.5820***	0.2700***
$DPT4_{t-2}$	-0.0825	-0.4644***
$DPT5_t$	0	0
$DPT5_{t-1}$	0	0
$DPT5_{t-2}$	0	0
DPR_t	-0.4668*	-0.0429
DPR_{t-1}	0.0624	0.8993***
DPR_{t-2}	0.1535	-0.0187
Control variable	Control	Control
Stock	Control	Control
Year	Control	Control
Wald chi2	455.74	352.23
P	0.0000	0.0000

According to the regression results of the influencing factors of volatility in Table 6, this article holds that the increase of media attention has attracted the attention of investors, resulting in the intensification of stock volatility in the current period. Thus, Hypothesis 1b is verified, which is consistent with the research results of Huberman and Regev (2001), Bhattacharya et al. (2009) and Van Heerde et al. (2015) on the impact of media attention on stock volatility. That is, media attention will lead to stock volatility. In this paper, the change of media sentiment has no impact on the stock volatility, denying hypothesis 2b. We believe that the positive change of public sentiment in the current period will lead to the increase of current volatility, and volatility will reverse in the future. The positive change of sentiment in the current period may make investors raise their expectations for stocks, resulting in more frequent buying and increased stock volatility. Thus, Hypothesis 3b is verified, and the research results are consistent with the research results of Zhi Da et al. (2015). The change of theme will attract the attention of investors, and investors need a certain reaction time for the change of theme. The regression results show that the emergence of the Chinese attitude and influence outlook theme will lead to the increase of future volatility, and the emergence of the public attitude theme will lead to the decline of current and future volatility. The emergence of the theme of international relations has a positive impact on current volatility, leading to the decline of future volatility in the first period, and the increase of future volatility in the next two periods, and the change of the development theme has no impact on the volatility of relevant stocks. Therefore, the change of public opinion theme has a significant impact on volatility, which verifies Hypothesis 4b. The research results based on the prospect theory value in this article show that the positive change of the prospect theory value in the current period will increase the volatility of the stock. The theoretical value of high prospect is more attractive to investors, leading to overbuying and higher volatility, which verifies Hypothesis 5b.

5. Robustness test

In order to ensure that the conclusion of this paper is robust rather than the contingency caused by a single explained variable, this paper chooses other methods to calculate the stock return and volatility. The yield used in the previous article is simple yield, and the volatility is the historical 5-day volatility. In this part, the return rate is replaced by the logarithmic return rate, and the volatility rate is replaced by the historical ten-day volatility rate. The calculation formula is as Eq (1), where n becomes 10. Table 7 reports the regression results using alternative variables. It can be seen from the table that the regression result of the yield is consistent with the above. In the regression result of the volatility, the change of media attention has the ability to predict future volatility, the change of media sentiment has a positive impact on future volatility, and the positive change of prospect theoretical value can predict the improvement of future volatility. The results in Table 7 are basically consistent with the original hypothesis, which further supports the hypothesis in this paper.

6. Conclusions

Taking the online public opinion factors based on text mining, the investor psychological factors based on prospect theory and the return and volatility of stocks related to Japan’s nuclear wastewater incident as the research object, we explore the impact of online public opinion related factors and investors’ psychological factors on the performance of related stocks under the background of the Japanese nuclear wastewater discharge incident.

The results confirm that under the background of the Japanese nuclear wastewater discharge incident, online public opinion has an impact on stock performance. After the exposure of the Japanese nuclear wastewater incident, the media reports attracted the attention of investors, so the frequency of media reports significantly impacts investors. Media news can quickly and accurately convey information and emotions to investors, so the change of media sentiment immediately impacts investors’ cognition, which is then reflected in the stock market. The change of media sentiment when reporting Japan’s nuclear wastewater affects investors’ cognition and emotions in real time. Most studies believe that positive media sentiment is one of the reasons for the increase of stock return. The research of this article shows that the positive change of media sentiment will lead to the decline of stock return. In the context of the negative event of nuclear wastewater in Japan, the increase of media attention will aggravate the negative impression of investors in relevant stocks, leading to the reduction of stock returns. The rapid spread of information and emotion in the online message board and the continuous interaction of the message board will lead to changes in public sentiment, which will impact the current and future stock performance. The change in the theme of public opinion represents the structural change in the content of investors' attention and reflects the change in attention and psychology. Due to the limited attention, the change of public opinion theme can contribute to the effective prediction of stock performance to a certain extent. Changes in different public opinion themes have different impacts on stock performance. Changes in themes of government attitudes and public attitudes and themes that affect the public have impacts on stock performance, while topics that are not closely related to the public, such as the theme of development in this article, have no significant impact on stock performance. Behavioral finance believes that investors are irrational, and the prospect theory has been unanimously recognized by the financial circles. Moreover, investors will make irrational decisions because of their own cognition and regret aversion. When investors face stocks related to the Japanese nuclear wastewater incident, they will not only be affected by the current public opinion but also refer to the past earnings of stocks.

In the emergency scenario, we put the online public opinion factors and psychological factors into the same framework, which provides a new perspective for the study of the stock market. For practical significance, the research results of this article show that a correlation exists between online public opinion and the performance of the stock market. Paying attention to and mastering the change of public opinion theme and mood, and stabilizing the mood of media reports make a certain contribution to promoting the rational management of online public opinion and the stable operation of the financial market. It provides theoretical support for the prevention and governance of government online public opinion. For the government, after the occurrence of a public emergency, it needs to control the media report and issue the statement of the relevant industry first, so as to ease the mood of public opinion, control the theme of public opinion and prevent the crisis from spreading to the financial market. In addition, the research method of this article can prompt financial departments and investors to pay attention to the impact of network public opinion on relevant stocks, analyze the online public opinion caused by emergencies, observe the emotional stability of media reports, pay attention to the changes of public opinion topics and predict the change trend of public sentiment, which can help investors make or change investment decisions in time, gain profits and avoid losses.

However, the current study has the following limitations. The data sources used in this article cannot completely cover all media and the public. Moreover, due to technical limitations, the LDA model selected in this article has some subjectivity. Therefore, future research can use more comprehensive data and more advanced machine learning methods to improve the scientific research.

Acknowledgments

This research is supported by the National Social Science Fund of China (Grant No. 21BGL215).

Conflict of interest

All authors disclosed no relevant relationships.

References

1. B. Wang, S. Zhang, J. Dong, Y. Li, Y. Jin, H. Xiao, et al., Ambient temperature structures the gut microbiota of zebrafish to impact the response to radioactive pollution, *Environ. Pollut.*, **293** (2022), 118539. https://doi.org/10.1016/j.envpol.2021.118539
2. K. Liu, J. Zhou, D. Dong, Improving stock price prediction using the long short-term memory model combined with online social networks, *J. Behav. Exp. Finance*, **30** (2021). https://doi.org/10.1016/j.jbef.2021.100507
3. Y. Lv, J. Piao, B. Li, M. Yang, Does online investor sentiment impact stock returns? Evidence from the Chinese stock market, *Appl. Econ. Lett.*, **29** (2022), 1434–1438. https://doi.org/10.1080/13504851.2021.1937490
4. G. Huberman, T. Regev, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *J. Finance*, **56** (2001), 387–396. https://doi.org/10.1111/0022-1082.00330
5. U. Bhattacharya, N. Galpin, R. Ray, X. Yu, The role of the media in the internet IPO bubble, *J. Finance Quant. Anal.*, **44** (2009), 657–682. https://doi.org/10.1017/S0022109009990056
6. H. J. V. Heerde, E. Gijsbrechts, K. Pauwels, Fanning the flames? how media coverage of a price war affects retailers, consumers, and investors, *J. Mark. Res.*, **52** (2015), 674–693. https://doi.org/10.1509/jmr.13.0260
7. L. Fang, J. Peress, Media coverage and the cross-section of stock returns, *J. Finance*, **64** (2009), 2023–2052. https://doi.org/10.1111/j.1540-6261.2009.01493.x
8. P. C. Tetlock, Giving content to investor sentiment: The role of media in the stock market, *J. Finance*, **62** (2007), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x
9. J. Engelberg, Costly information processing: evidence from earnings announcements, *AFA 2009 San Francisco Meetings Paper*, 2008. http://dx.doi.org/10.2139/ssrn.1107998.
10. H. Du, J. Hao, F. He, W. Xi, Media sentiment and cross-sectional stock returns in the Chinese stock market, *Res. Int. Bus. Finance*, **60** (2022), 101590, https://doi.org/10.1016/j.ribaf.2021.101590
11. M. W. Uhl, The Long-run impact of sentiment on stock returns, Working Paper, 2011.
12. M. T. Suleman, Stock market reaction to good and bad political news, *Asian J. Finance Account.*, **4** (2012), 299–312. https://doi.org/10.5296/ajfa.v4i1.1705
13. G. W. Brown, M. T. Cliff., Investor sentiment and the near-term stock market, *J. Empir. Finance*, **11** (2004), 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001
14. J. Wurgler, M. Baker, Investor sentiment and the cross-section of stock returns, *J. Finance*, **61** (2006), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x
15. F. M. Statman, Investor sentiment and stock returns, *Finance Anal. J.*, **56** (2000), 16–23. https://doi.org/10.2469/faj.v56.n2.2340
16. Z. Li, S. Wang, M. Hu, International investor sentiment and stock returns: Evidence from China, *Invest. Anal. J.*, **50** (2021), 60–76. https://doi.org/10.1080/10293523.2021.1876968
17. Y. Kim, K. Y. Lee, Impact of investor sentiment on stock returns, *Asia-Pac. J. Finance Stud.*, **51** (2022), 132–162. https://doi.org/10.1111/ajfs.12362
18. T. Renault, Intraday online investor sentiment and return patterns in the US stock market, *J. Bank Finance*, **84** (2017), 25–40. https://doi.org/10.1016/j.jbankfin.2017.07.002
19. E. Bartov, L. Faurel, P. S. Mohanram, Can twitter help predict firm-level earnings and stock returns?, *Account. Rev.*, **93** (2018), 25–57. https://doi.org/10.2308/accr-51865

20. Y. Shynkevich, T. M. Mcginnity, S. Coleman, A. Belatreche, Stock price prediction based on stock-specific and sub-industry-specific news articles, in *2015 International Joint Conference on Neural Networks (IJCNN)*, (2015), 1–8. https://doi.org/10.1109/IJCNN.2015.7280517
21. H. Yun, G. Sim, J. Seok, Stock prices prediction using the title of newspaper articles with Korean natural language processing, in *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, (2019). https://doi.org/10.1109/ICAIIC.2019.8668996
22. M. Zhang, J. Yang, M. Wan, X. Zhang, J. Zhou., Predicting long-term stock movements with fused textual features of Chinese research reports, *Expert Syst. Appl.*, **210** (2022), 118312. https://doi.org/10.1016/j.eswa.2022.118312
23. N. Barberis, M. Huang, Stock as lotteries: The implications of probability weighting for security prices, *Am. Econ. Rev.*, **98** (2008), 2066–2100. https://doi.org/10.1257/aer.98.5.2066
24. B. Boyer, T. Mitton, K. Vorkink, Expected idiosyncratic skewness, *Rev. Finance Stud.*, **23** (2010), 169–202. https://doi.org/10.1093/rfs/hhp041
25. T. G. Bali, N. Cakici, R. F. Whitelaw, Maxing out: Stock as lotteries and the cross-section of expected returns, *J. Finance Econ.*, **99** (2011), 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014
26. J. Conrad, R. F. Dittmar, E. Ghysels, Ex ante skewness and expected stock returns, *J. Finance*, **68** (2013), 85–124. https://doi.org/10.1111/j.1540-6261.2012.01795.x
27. N. Barberis, A. Mukherjee, B. Wang, Prospect theory and stock returns: An empirical test, *Rev. Finance Stud.*, **29** (2016), 3068–3107. https://doi.org/10.1093/rfs/hhw049
28. J. Wang, C. Wu, X. Zhong, Prospect theory and stock returns: Evidence from foreign share markets, *Pac.-Basin Finance J.*, **69** (2021), 101644. https://doi.org/10.1016/j.pacfin.2021.101644
29. A. J. N. Junior, M. C. Klotzle, L. E. T. Brandão, A. C. F. Pinto, Prospect theory and narrow framing bias: Evidence from emerging markets, *Q. Rev. Econ. Finance*, **80** (2021), 90–101. https://doi.org/10.1016/j.qref.2021.01.016
30. X. Yang, D. Gu, J. Wu, C. Liang, Y. Ma, J. Li, Factors influencing health anxiety: The stimulus–organism-response model perspective, *Internet Res.*, **31** (2021), 2033–2054. https://doi.org/10.1108/INTR-10-2020-0604
31. Z. Tang, M. Warkentin, L. Wu, Understanding employees' energy saving behavior from the perspective of stimulus-organism-responses, *Resour. Conserv. Recycl.*, **140** (2019), 216–223. https://doi.org/10.1016/j.resconrec.2018.09.030
32. B. J. Bushee, J. E. Core, W. Guay, S. Hamm, The role of the business press as an information intermediary, *J. Account. Res.*, **48** (2010), 1–19. https://doi.org/10.1111/j.1475-679X.2009.00357.x
33. Z. Da, J. Engelberg, P. J. Gao, In search of attention, *J. Finance*, **66** (2011), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x
34. F. Comiran, T. Fedyk, J. Ha, Accounting quality and media attention around seasoned equity offerings, *Int. J. Account. Inf. Manage.*, **26** (2017), 443–462. https://doi.org/10.1108/IJAIM-02-2017-0029
35. W. S. Chan., Stock price reaction to news and no-news: drift and reversal after headlines, *J. Finance Econ.*,**70** (2003), 223–260. https://doi.org/10.1016/S0304-405X(03)00146-6
36. P. C. Tetlock, M. Saar-Tsechansky, S. Macskassy, More than words: Quantifying language to measure firms' fundamentals, *J. Finance*, **63** (2008), 1437–1467. https://doi.org/10.1111/j.1540-6261.2008.01362.x

37. P. Jiao, A. Veiga, A. Walther, Social media, news media and the stock market, *J. Econ. Behav. Organ.*,**176** (2020), 63–90. https://doi.org/10.1016/j.jebo.2020.03.002
38. T. Huang, X. Zhang, Industry-level media tone and the cross-section of stock returns, *Int. Rev. Econ. Finance*, **77** (2021), 59–77. https://doi.org/10.1016/j.iref.2021.09.002
39. Y. He, L. Qu, R. Wei, X. Zhao, Media-based investor sentiment and stock returns: A textual analysis based on newspapers, *Appl. Econ.*, **54** (2022), 774–792. https://doi.org/10.1080/00036846.2021.1966369
40. W. Wang, C. Su, D. Duxbury, The conditional impact of investor sentiment in global stock markets: A two-channel examination, *J. Bank Finance*, **138** (2022), 106458. https://doi.org/10.1016/j.jbankfin.2022.106458
41. R. B. Cohen, C. Polk, T. Vuolteenaho, The price is (almost) right, *J. Finance*, **64** (2009), 2739–2782. https://doi.org/10.1111/j.1540-6261.2009.01516.x
42. Z. Da, J. Engelberg, P. Gao, The sum of all FEARS investor sentiment and asset prices, *Rev. Finance Stud.*, **28** (2015), 1–32. https://doi.org/10.1093/rfs/hhu072
43. H. Yang, D. Ryu, D. Ryu, Investor sentiment, asset returns and firm characteristics: Evidence from the Korean stock market, *Invest. Anal. J.*, **46** (2017), 1–16. https://doi.org/10.1080/10293523.2016.1277850
44. J. Li, Y. Zhang, L. Wang, Information transmission between large shareholders and stock volatility, *N. Am. Econ. Finance*, **58** (2021), 101551. https://doi.org/10.1016/j.najef.2021.101551
45. M. Ammann, R. Frey, M. Verhofen, Do newspaper articles predict aggregate stock returns?, *J. Behav. Finance*, **15** (2014), 195–213. https://doi.org/10.1080/15427560.2014.941061
46. F. Wong, Z. Liu, M. Chiang, Stock market prediction from WSJ: text mining via sparse matrix factorization, in *Proceedings of the 2014 IEEE International Conference on Data*, (2014), 430–439. https://doi.org/10.48550/arXiv.1406.7330
47. N. C. Barberis, Thirty years of prospect theory in economics: A review and assessment, *J. Econ. Perspect.*, **27** (2013), 173–195. https://doi.org/10.1257/jep.27.1.173
48. D. Kahneman, A. Tversky, Prospect theory: An analysis of decision under risk, *Econometrica*, **47** (1979), 263–291. http://www.jstor.org/stable/1914185
49. H. Chen, P. De, Y. Hu, B. H. Hwang, Wisdom of crowds: The value of stock opinions transmitted through social media, *Rev. Finance Stud.*, **27** (2013), 1367–1403. https://doi.org/10.1093/rfs/hhu001