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DO EMOTIONAL STRATEGIES WORK? EVIDENCE FROM RUMOR CLARIFICATION ANNOUNCEMENT

Peinan JI[1], Hui JI[1], Linke GUO[1], Xiaojuan YANG[1]✉, Yang HAN[2]

[1]*School of Management, Lanzhou University, Lanzhou, China*
[2]*LiaoNing Administraters College of Police and Justice, Shenyang, China*

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Abstract. Financial markets are filled with rumors because of information asymmetry. Although issuing clarification announcements is the most straightforward approach for organizations, previous research has mostly focused on analyzing the influence of rumors and the heterogeneity of their clarification statements on the efficacy of rumor management. This study investigates how mood elements influence the effectiveness of 335 rumor clarification statements in China's A-share market from 2019 to 2023. By employing textual sentiment analysis, event study method, and fixed-effects regression models, the primary results indicate that rumors vary in their characteristics and have diverse effects on stock price volatility. Furthermore, we find that clarification announcements effectively restore stock values, though their influence on negative rumors is somewhat restricted. Announcements with a positive mood greatly improve the effectiveness of clarification, particularly when addressing favorable rumors. The level of transparency and the characteristics of the firm's information influence the impact of sentiment. Furthermore, the positive impact of sentiment is more noticeable in firms that are extremely transparent or not owned by the state.

Keywords: clarification announcements, event study method, text analysis, emotional language, emotional strategies, rumors.

JEL Classification: M1, M41, G14.

✉Corresponding author. E-mail: ***yangxiaojuan@lzu.edu.cn***

1. Introduction

The Internet has greatly altered the environment for generating and disseminating information, driven by the information revolution. This change has resulted in a significant transformation in the role of the public, shifting them from being passive recipients of information to becoming active distributors of information and creators of news content. As a result, spreading rumors has shifted from the original one-to-one model to a more expansive one-to-many model (Ke et al., 2022). Meanwhile, the formation of the digital media ecosystem has further exacerbated the challenges of rumor management, as it facilitates the rapid dissemination of emotional information through the utilization of AI and personalized recommendation algorithms. Although these technologies have enhanced the efficiency and reach of information dissemination, they have also, to some extent, amplified the impact of rumors, enabling false information to reach susceptible populations more precisely, thereby accelerating the speed of rumor propagation and expanding its scope of influence. Against this backdrop, the surging stock market has garnered increasing interest from investors and the general public. Nevertheless, despite the notable accomplishments in the development of China's stock market, the deficiencies in the information disclosure system continue to pose a substantial obstacle (Tan et al., 2023), and social media platforms have also become a fertile environment for the proliferation and dissemination of market rumors (Jia et al., 2020). These rumors have the potential to not only disturb the market order (Pal et al., 2017), but also significantly harm the value of listed companies (Ahern & Sosyura, 2015), particularly by affecting share prices and undermining investor confidence (Zhang et al., 2022a). In response to rumors, publicly traded firms have established a custom of providing clarification statements. However, the impact of these statements varies based on aspects such as media choice, content, language, format, and timing (Agarwal et al., 2022; Wang et al., 2022; Yang, 2020). Hence, it is imperative to analyze the aspects that influence the efficacy of clarification announcements in order to maximize their value.

The widespread discussion of the impact of market rumors and their clarifications on market operations has grown prominent in the contemporary era of information explosion. Nevertheless, there is a noticeable absence of focused investigation into the correlation between market rumors and explanation announcements, particularly a comprehensive examination of the emotional aspect. This study seeks to address the lack of research by examining the impact of emotional components in clarification announcements made by listed firms. The goal is to understand how these aspects subtly alter and influence the effectiveness of the clarifications, with the purpose of identifying reliable cognitive reference points in times of market uncertainty. The emotional tone is a core element of clarification announcements, exerting a profound influence on investor behavior through psychological mechanisms such as cognitive dissonance. When the information in announcements deviates from investors' existing cognitions or expectations, cognitive dissonance arises. To alleviate this discomfort, investors may adjust their cognitions, attitudes, or behaviors. The emotional tone plays a crucial role here: if it aligns with investors' expectations, it may reinforce their judgments and prompt them to buy or hold; if it does not, it may lead to confusion or unease, prompting them to sell or seek other opportunities. These psychological mechanisms directly guide investors' decisions to buy or sell, influencing stock market fluctuations. Due to the swift advancement of technology, particularly the refinement of natural language processing (NLP) and text mining methods, we now possess the capability to examine and analyze unorganized material that was previously difficult to access, such as extensive web data and live social media remarks (Zhu et al., 2023). Wang et al. (2021) employ a text classification algorithm to automatically identify positional responses to debunking postings in user comments. Rubin (2017) discusses the application of text analytics to enhance the ability to identify dishonesty. Text analytics streamlines data acquisition and preprocessing while also providing researchers with advanced analytical tools such as detailed word frequency statistics and sentiment tendency analysis. This allows for a thorough exploration of the underlying sentiment in the text.

As a result, this paper adopts a two-track research strategy: on the one hand, we classify the rumors based on their nature and use the event study method to systematically examine the impact of clarification announcements on stock market returns under different rumor scenarios, aiming to reveal the specific mechanism of clarification announcements in calming market volatility. However, we conduct a thorough analysis of the emotional tone in clarification announcements using the technique of text sentiment analysis. We then employ the fixed-effects regression model to precisely measure the impact of emotional factors on the effectiveness of clarification. This approach aims to uncover the underlying logic and theoretical mechanism behind the phenomenon. Additionally, this research takes a novel approach by examining the impact of corporate information transparency and corporate nature on the sentiment effect of clarification announcements. It investigates how these external elements interact and, together, influence the ultimate clarification effect.

This paper contributes to research in three main ways. Firstly, from a theoretical standpoint, this study explores the role of emotional factors in corporate rumor management, incorporating emotional factors into the framework for analyzing the effectiveness of clarifications, thereby expanding the research scope of clarification announcements. By utilizing text analysis and web crawling techniques to conduct emotional analysis of announcements, the study broadens the relevant research horizon and provides a new theoretical perspective and empirical evidence for understanding the complex relationship between market rumors and clarification mechanisms. Furthermore, this paper's findings offer valuable insights into how listed companies can enhance the effectiveness of their clarification announcements when addressing various types of market rumors. It also highlights the importance of adjusting the emotional tone of these announcements to optimize their impact, thereby protecting the company's reputation and maintaining market stability. Finally, this study emphasizes the critical importance of corporate information openness and its impact on the clarification process. This serves as a valuable guide for regulators in developing information disclosure policies and safeguarding the rights and interests of investors. The second section of this paper comprises the literature review and the hypothesis. The third section deals with he data and methodology. Finally, the results and conclusions are presented.

2. Literature review and hypothesis development

2.1. Impact of rumors on stock price volatility

Unverified information, known as rumors (Wang et al., 2020; Zubiaga et al., 2018), can significantly influence the market. Some scholars who study rumors concentrate on analyzing rumor propagation models (Li et al., 2019; Tian & Ding, 2019). They simulate the dynamics of rumor spread using different methodologies (Ke et al., 2022; Liu et al., 2019) and aim to develop strategies to manage the spread of rumors based on these models (Zhang et al., 2023). Another group of researchers concentrates on analyzing the influence of rumors on financial markets, specifically the stock market (Tavor, 2013). We can elucidate the relationship between rumors and stock price volatility by considering the viewpoints of information asymmetry theory, market efficiency theory, and behavioral finance. According to the theory of information asymmetry, rumors serve as a means of creating an imbalance in the availability of information. This puts small and medium-sized investors at a considerable disadvantage compared to large institutions in terms of how quickly they can access information, the range of information they have access to, and their ability to analyze it. Consequently, individual investors find it challenging to differentiate between trustworthy and untrustworthy information (Yang & Luo, 2014). Consequently, they are more likely to make illogical investing choices in response to market rumors (Lin et al., 2013). This irrational behavior ultimately influences stock prices, leading to anomalous price volatility and deviations from their intrinsic values. The theory of market efficiency posits that the market promptly responds to and integrates all accessible information (Fama, 1991), hence influencing stock prices. Nevertheless, the presence of rumors might momentarily hinder market efficiency as the uncertainty surrounding them delays the quick reflection of their true value in market pricing. Once the rumors either confirm or disprove, the transient and illogical fluctuations in pricing typically return to rational levels. The perspective of behavioral finance, however, focuses on the influence of investor psychology and behavior on market volatility. Behavioral finance suggests that when faced with uncertainty and insufficient information, investors often display irrational behavior (Cai et al., 2023), which can magnify the influence of rumors on stock prices (Zhang et al., 2022a).

Moreover, the characteristics of rumors exhibit substantial disparities in their influence on financial markets (Ji et al., 2024). Consensus among scholars indicates that good rumors typically result in an increase in stock prices and generate positive, abnormal returns. Conversely, negative rumors tend to lead to a decline in stock prices and produce negative abnormal returns (Zhang & Wang, 2024). Within China's securities market, it is typical for listed companies to employ the tactic of issuing clarification announcements in response to false rumors that are circulating (Ji et al., 2020). The objective is to counteract the negative impact of these rumors and restore stability to the stock price. Nevertheless, it is important to acknowledge that the efficacy of clarifying announcements is not universally applicable but rather heavily influenced by the characteristics of the rumors. Clarification announcements made in response to negative rumors often have a limited impact on clarifying the situation, which makes it challenging to restore market confidence promptly. Conversely, the market may already have a partial understanding of the clarifications made in response to positive rumors. However, timely and accurate clarification announcements may still contribute to strengthening the market's positive perception of the company. Therefore, based on previous research, this study proposes the following hypothesis H1:

H1: Market rumors can lead to anomalous fluctuations in stock prices. The effect of rumors can vary depending on their nature, with positive and neutral rumors resulting in positive deviations in stock prices, while negative rumors lead to negative deviations.

2.2. Effectiveness of clarification announcements and their reaction to rumors

A clarification announcement refers to a formal declaration or explanation made to address a false rumor or misunderstanding that is circulating in the market. Clarification can lead to an adjustment process (Radechovsky et al., 2019). In the context of public corporations, these announcements typically try to correct market assumptions or false information regarding the company's operations, finances, management, or other significant topics. When there is unequal access to information, rumors may impact market players' investment choices, leading to changes in stock price volatility. Investors often rely on information and news to make well-informed decisions. However, the appearance of rumors often generates confusion, panic, and doubt, which may result in investors making unwise investment choices (Alzahrani et al., 2023). Clarification announcements serve to mitigate information uncertainty caused by market rumors, improving the market's logical view of a company's actual value and pricing.

The purpose of rumor clarification is to mitigate the impact of asymmetric information and aberrant stock returns by enhancing information transparency. However, the success of this approach is uncertain. According to Voas (2002), promptly addressing rumors is highly significant. While Wang et al. (2019) demonstrate that investors frequently display irrational behavior, contemporary behavioral finance research relates the lack of randomness in stock volatility to the cognitive and emotional biases of investors. Confirming the truthfulness of rumors might result in heightened fluctuations in investor sentiment, which may trigger impulsive investment decisions and greater instability in stock prices. The efficiency of clarifying announcements is a topic of contention, possibly due to variations in the characteristics of rumors.

As a result, this study categorizes rumors into three types: good rumors, negative rumors, and neutral rumors, depending on their impact on the firm as determined by their nature (Ji et al., 2020). In their study, Ji et al. (2024) show that clarification announcements have a more pronounced impact on positive and neutral rumors compared to negative rumors. Xu et al. (2020) show that when a company provides clear and precise information, it counteracts the impact of rumors. However, the resolution of rumors limits this effect. In their study, they found that corporate clarification had a compensatory, albeit limited, impact following the resolution of rumors. Announcements that provide an explanation have a notable impact on reducing the positive anomalous returns resulting from optimistic rumors, but their effect on bearish stock prices is not statistically significant. Jia et al. (2017) find in their study that reliable sources tend to report on unfavorable rumors. This, in turn, leads to an increase in prejudice against the targeted firms in the media. To address negative rumors that arise in media reporting, companies should release technical explanation statements. In their study, Wang and Song (2015) demonstrate that the presence of positive content in media reports does not have a favorable influence on the effectiveness of debunking rumors. However, they found that the inclusion of negative content in debunking arguments boosts their impact. This demonstrates the importance for companies to promptly release clarification statements that are both comprehensive and optimistic in response to the detrimental effects of market rumors. Thus, drawing from prior studies, this paper presents the following hypothesis H2:

H2: Clarification announcements have a positive impact on stock prices, but the effectiveness of clarifying rumors depends on their nature. Clarification announcements for positive rumors are the most effective, whereas clarification announcements for negative rumors do not hold market validity.

2.3. The influence of emotional factors on the effectiveness of clarification announcements

Because of the rapid advancement of the Internet, an increasing number of people are expressing their opinions on online platforms. The exponential growth of user-generated content has rendered manual analysis arduous, prompting the adoption of information technology in text sentiment mining as a viable solution (Do et al., 2019). Text sentiment analysis is the systematic examination and interpretation of emotional patterns in text using technical methods. Based on the different degrees of analysis, we can categorize text sentiment analysis into three categories: word level, sentence level, and chapter level (Xu et al., 2019b). Word-level sentiment analysis is a study that specifically examines the sentiment expressed by individual words. Accurately analyzing vocabulary sentiment forms the foundation for sentence- and chapter-level sentiment analysis. Additionally, an increasing number of firms utilize text analysis to assess the tone and mood of investor message boards (Loughran & McDonald, 2011).

Sentiment analysis is the process of classifying a given text's polarity, namely determining whether the conveyed views in the text are positive, negative, or neutral (Abdi et al., 2019). It has the ability to expose the fundamental attitudes that an entity maintains (Soleymani et al., 2017). Sentiment analysis enables the quantification and study of emotions in news reports, facilitating a deeper comprehension and explanation of the influence of news events on public sentiment (Shapiro et al., 2022). Furthermore, sentiment analysis has emerged as a crucial analytical instrument in other domains, including politics, business, advertising, and marketing (Rezaeinia et al., 2019). Zhang et al. (2022b) emphasize that the content of messages that debunk rumors plays a crucial role in determining the communication threshold. Meanwhile, Li et al. (2021) employ natural language processing techniques to construct a regression model for investigating the connection between the content of microblogs that debunk rumors and the efficacy of debunking. The system identifies sentiment inclinations, such as positive, neutral, or negative emotions (Mantyla et al., 2018), in textual information such as social media posts, news articles, and financial remarks. The analysis of sentiment patterns is critical for anticipating the stock market's fluctuations following a clarification announcement (Xing et al., 2018; Xu et al., 2019a). Specifically, it involves examining how the degree of sentiment in a clarification announcement influences its effectiveness in providing clarity.

In summary, the use of varying degrees of emotion in clarification announcements leads to distinct outcomes. It is widely accepted that a corporation can enhance its effectiveness in dispelling rumors by employing positive language, an exaggerated tone, positive emotions, and a suitable mindset. The impact of rumors varies depending on their type. Investors may effectively accept and trust good rumors when the explanation statement reflects positive emotions. Conversely, by appropriately expressing emotions in the announcement, corporations may clarify unfavorable rumors and mitigate their impact. However, if corporations fail to consider objective reality and instead emphasize emotional reasons in their clarification announcements, they run the risk of causing investors to feel resentful, lose faith, or render the clarification announcements ineffective. Thus, this paper puts forward the subsequent hypothesis H3:

H3: The emotional components of explanation announcements influence their impact. Positive emotions increase the impact of clarification announcements, and this effect is most pronounced when dispelling positive rumors.

3. Research design

3.1. Samples and data

3.1.1. Sample selection and processing

This study aims to examine the influence of sentiment elements in clarification announcements on their effectiveness in providing clarification. We leveraged the China Stock Market & Accounting Research Database (CSMAR) to obtain the required stock return and SZSE 300 index data. Furthermore, the China Securities Regulatory Commission (CSRC) designated the Juchao Information Network as a website for information disclosure, which I accessed to clarify announcements made by listed businesses. The investigation includes data from January 1, 2019, to December 31, 2023. The rationale for selecting these specific five years of data for the study is twofold. Firstly, there is a greater abundance of rumor samples during the epidemic period compared to other time periods. Second, there is a higher frequency of rumor clarification announcements, and companies are more inclined to engage in clarification behaviors due to the adverse external economic conditions resulting from the epidemic outbreak.

We conduct a screening process on the obtained samples to exclude any that do not satisfy the predetermined criteria. Initially, we remove samples from listed companies labeled with ST or *ST, which delist when they make announcements to dispel rumors. This measure aims to avert unpredictable stock price fluctuations due to exceptional events and unavoidable consequences before delisting. Furthermore, we eliminated samples that issued explanation announcements subsequent to the initial clarification announcement, as well as samples that were unable to establish the timing of the rumor. Subsequently, we eliminate samples that do not have an adequate time period for estimation between the listing date and the date of the clarification announcement. Additionally, we exclude samples with rumors that have occurred multiple times within the past three months, as these frequent occurrences may render the rumors ineffective in influencing the stock price. Ultimately, we eliminate samples that have incomplete financial data. In the initial phase of the investigation, we focus exclusively on samples that occur within a three-day period from the occurrence of the rumor to the day of the clarification statement. In conclusion, we acquired a total of 335 valid samples. The regression analysis part includes all samples without exception.

3.1.2. Sample grouping

We refer to the study by Ji et al. (2020), which grouped rumors according to their nature and classified them into three sub-sample groups: positive rumors, negative rumors, and neutral rumors. The positive rumors are characterized by keywords such as increased profitability, transformation of losses into profits, securing new orders, restructuring of assets, back-door listing, advancement in new technologies, expansion into new markets, establishment of new factories, attracting strategic investors, overall listing, asset acquisition, and asset injection. Negative rumors encompass a range of allegations such as violation, manipulation, falsehood, misrepresentation, exaggeration, fraud, deception, forgery, bribery, embezzlement, misappropriation, infringement of privileges, loss of state-owned assets, smuggling, misappropriation of funds, misappropriation of public funds, crime, tax evasion, detention, arrest, sentencing, concealment of material matters, misleading statements, insider trading, expulsion from the party, expulsion from public office, and others. It is impossible to ascertain the market impact of a rumor and designate it as neutral, as it is neither beneficial nor negative. For instance, the rumor suggesting that the company's shareholders' meeting will result in the replacement of the board of directors is considered a rumor with a neutral connotation. We gathered a total of 335 rumor samples after conducting a thorough screening and classification process. We categorized these samples into 87 positive rumors, 179 negative rumors, and 69 neutral rumors based on their nature.

We categorized the listed firms based on their level of information openness and employed the disclosure evaluation as a metric to evaluate their corporate information transparency. We place any rating falling under the A or B category, representing excellent or good, in the high information transparency group. We classify ratings not falling under this category as part of the low-information disclosure group. After screening and categorizing the samples, we found 234 samples with high corporate information openness and 101 samples with low corporate information transparency.

We categorize enterprises based on the nature of their equity, using SOEs as a classification criterion for those with SOEs equity and classifying the remaining enterprises (private, foreign, etc.) as non-SOEs. We identified 84 SOEs and 251 non-SOEs based on the screening and categorization of the samples.

3.2. Research model setting

3.2.1. Event study method

The event date and window period are defined as follows: The rumor event date (TR) is the date when the rumor is first circulated, and the window period is defined as [TR-10, TR]. The clarification event date (TC) is the date when the official announcement is made to address the rumor, and the window period is defined as [TC-3, TC+3]. This study selects a 150-day trading period prior to the rumor event date as the estimating period, in order to predict the normal return of the stock.

Following Betton et al. (2018), we employ a market modeling methodology to calculate abnormal returns. The capital asset pricing model (CAPM) is used to predict the anomalous rate of return, as represented by Equation (1):

$$R_{it} = \alpha_{it} + \beta_{it} \cdot R_{mt} + {}_{it}. \quad (1)$$

R_{it} refers to the average rate of return of the ith stock on day t, while R_{mt} refers to the average market rate of return on day t. For this study, we use the SZSE 300 index as a replacement.

The daily abnormal return of the stock, denoted as AR_{it}, is computed using the market-adjusted technique, as represented by Equation (2):

$$AR_{it} = R_{it} - \alpha_i - \beta_i \cdot R_{mt}. \quad (2)$$

The average abnormal return AAR_t for each day is then calculated, as shown in Equation (3):

$$AAR_t = \sum_{1=1}^{n} AR_{it} / n. \quad (3)$$

CAR_{it} denotes the cumulative abnormal return of stock i during the event window $\left[t1,\ t2\right]$. It is shown in Equation (4):

$$CAR_{it} = \sum_{i=1}^{n} AR_{it}. \quad (4)$$

$CAAR_{it}$ denotes the cumulative average abnormal returns of all stocks over the event window $\left[t1,\ t2\right]$. It is shown in Equation (5):

$$CAAR_{it} = \sum_{1=1}^{n} AAR_{it} / n. \quad (5)$$

3.2.2. Text sentiment analysis model

Sentiment scoring of clarification announcements of two types of rumors was performed by text word selection processing and sentiment analysis of the web crawler software GooSeeker respectively. The process has two main steps of clarification announcement word selection processing and sentiment analysis. The positive sentiment score is shown in Equation (6):

$$Score = \frac{pos}{pos + neg} \cdot 100\%, \quad (6)$$

Where *Score* is the final score, *pos* is the total frequency of positive words and *neg* is the total frequency of negative words.

3.2.3. Fixed-effects regression model

The following model was constructed to test the relationship between clarification emotion and clarification effect as shown in Equation (7):

$$\left|CAR_{i,j,t}\right| = \beta_0 + \beta_1 Score + \Sigma Controls_{i,j} + _{i,j}. \quad (7)$$

3.2.4. Variables

The paper's dependent variable is $\left|CAR\left(-3,3\right)\right|$, which is within a three-day time frame between the occurrence of the rumor and the date of the clarification statement. We exclusively consider samples within this specific time window. Table 1 indicates that we choose the control variables based on the perspective of the listed organizations, with the emotion *Score* serving as the independent variable. Based on research by Wu et al. (2022), this paper incorporates firm size (*Size*) and firm's total assets (*Asset*) as indicators of the listed company's size, return on net assets (*Roe*) as an indicator of the company's profitability, TobinQ (*TobinQ*) as an indicator of the enterprise's value, debt to asset ratio (*Debt*) as an indicator of the company's financial risk, and *Insv* as an indicator of institutional investors' attitude towards the company's long-term development. The model is estimated using the least-squares method.

Table 1. Description of the values of the variables

Variable classification	Variable symbol	Variable name	Variable description
Dependent variable	|CAR (–3,3)|	Cumulative Abnormal Returns	Abnormal returns for a total of seven days from three days before to three days after the date of the clarification announcement were calculated using the event study approach
Independent variable	Score	Sentiment Score	Ratio of the total frequency of positive words to the sum of the total frequency of positive and negative words
Control variables	Size	Firm Size	Logarithm of the company's total market capitalization, taken from the previous year's data
	Asset	Total Assets	Total assets of the company, taking the previous year's data and taking the logarithm of it
	Roe	Return on Net Assets	Net profit/total assets, taking the previous year's data
	TobinQ	Tobin's Q	Market capitalization/total assets, take the previous year's data
	Debt	Debt to Asset Ratio	Total liabilities / total assets, take the previous year's data
	Insv	Shareholding Ratio of Investment Institutions	Shareholding ratio of investment institutions, taking the previous year's data

4. Results

4.1. Impact of rumors on the stock market

Table 2 and Figure 1 display the mean anomalous returns of three subgroups with varying rumor characteristics, spanning from 10 days prior to the distribution of the rumor to the

Table 2. Impact of rumors on the stock market

AAR	Positive rumors (N = 87)	Negative rumors (N = 179)	Neutral rumors (N = 69)
0	0.0019728	0.000889	0.0042191
1	–0.0044263	–0.0017979	0.0029391
2	0.0061376	–0.0046904**	0.0044448
3	0.0054987	–0.0011883	0.0009314
4	0.0100985*	0.0009072	0.0013571
5	0.0034688	–0.0030346	0.0098672***
6	0.0015022	–0.0005489	0.0048656
7	0.0057175	–0.0015925	0.0119177***
8	0.0189783***	–0.0016576	0.0126347***
9	0.0330685***	–0.0083119***	0.0336809***

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

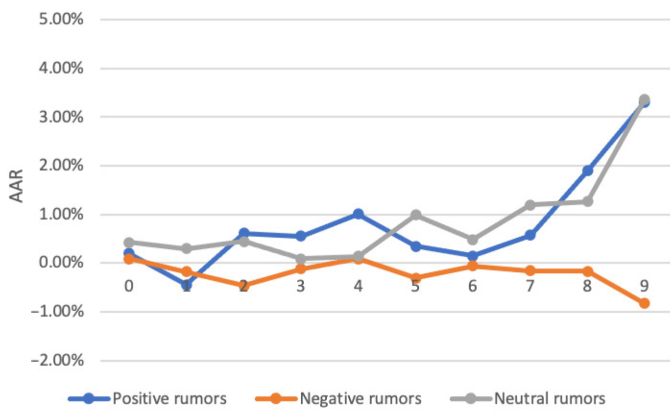

Figure 1. Impact of rumors on the stock market

actual release date. It is evident that on the date that the rumor was released, the average aberrant returns of the three subsamples achieved a statistical significance level of 1%. The mean abnormal returns of positive and neutral rumors are significantly positive, while the mean abnormal returns of negative rumors are significantly negative. This suggests that positive and neutral rumors result in upward stock price movements, with positive rumors having a more pronounced effect. Unfavorable rumors result in adverse changes in stock prices. Hypothesis H1 has been confirmed.

Further analysis of the research results shows that it has important practical significance for both investors and corporate management. When investors receive positive or neutral rumors, they tend to buy or hold stocks, expecting the stock prices to rise. Therefore, it is particularly important for short-term investors to timely capture and analyze market rumors. At the same time, companies should be aware of the significant impact of market rumors on stock prices, especially the positive impact of positive rumors. Management can guide market expectations and enhance company value through effective information disclosure strategies, such as publishing positive news and announcements. When faced with negative rumors, companies should quickly respond to stabilize stock prices.

4.2. Impact of clarification announcements on the stock market

Table 3 and Figure 2 exhibit the aggregate abnormal returns following the clarification statement. After the explanation announcements, the cumulative anomalous returns of the three subsamples are significant at 1%. Figure 2 demonstrates that both positive and neutral rumors' stock prices surged on the rumor day, only to revert to their initial levels following the announcement of clarifications. A comparison between the two reveals that the stock prices of positive rumors recovered to normal levels within 6 days, indicating a significant market

Table 3. Impact of clarification announcements on the stock market

CAAR	Positive rumors (N = 87)	Negative rumors (N = 179)	Neutral rumors (N = 69)
[0,0]	0.0056497	–0.0016306	0.0119006***
[0,1]	0.0189712***	–0.0032664	0.0246276***
[0,2]	0.0330748***	–0.0115133***	0.0583598***
[0,3]	0.0166486***	–0.0213622***	0.0580123***
[0,4]	–0.0152636***	–0.0258781***	0.0571334***
[0,5]	–0.0093045	–0.0279205***	0.0611567***
[0,6]	–0.0010605	–0.0303003***	0.0552056***
[0,7]	0.002034	–0.0325883***	0.0555854***
[0,8]	–0.0052605	–0.0334036***	0.0559084***
[0,9]	–0.0058182	–0.0339675***	0.0584236***

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

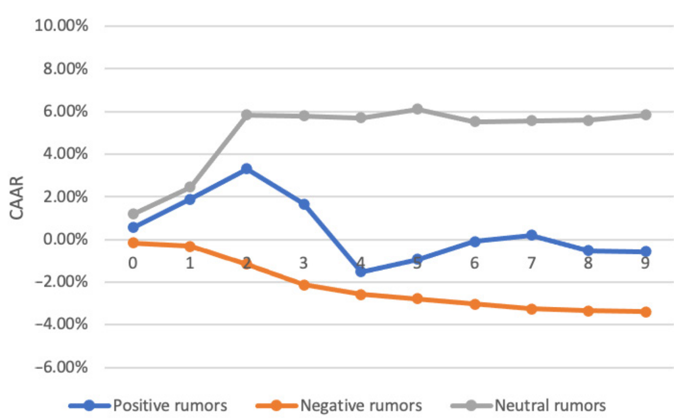

Figure 2. Impact of clarification announcements on the stock market

reaction to the clarification announcements. On the other hand, the stock prices of neutral rumors only experienced a weak recovery, suggesting that the clarification announcement did not have a significant impact. In contrast, the stock prices of adverse rumors persistently decline even after the release of the explanation, indicating the failure of the clarification announcement. We conduct experiments to verify Hypothesis H2.

Research results show that stock prices recover within 6 days after positive rumors are clarified, and the market reacts significantly, demonstrating the market's ability to quickly adjust to positive information. Neutral rumors result in a weaker recovery of stock prices, and the market reaction is not obvious. Although the long-term impact is small, short-term fluctuations increase transaction costs and risks. Therefore, investors need to strengthen the identification of information authenticity and ensure rapid response. When corporate management faces negative rumors, despite the limited effectiveness of clarifications, it still needs to respond quickly and transparently to control the decline in stock prices, protect the interests of shareholders, necessitating the establishment of a robust crisis management mechanism within the company.

4.3. Regression analysis of emotion degree and clarification effect of clarification announcement

4.3.1. Descriptive statistical analysis

Table 4 presents the descriptive statistics for the variables used in our regressions. The mean absolute value of the cumulative abnormal returns within the [–3, 3] window surrounding the date of the rumor clarification announcement, denoted as |CAR (–3,3)|, is 0.0795. This suggests that the market responds positively to rumor clarifications. The average score is 0.7147, indicating that rumor clarification announcements have a significant share of positive word frequency. The firm size (SIZE) has a mean of 21.3877 and a standard deviation of 4.4874, suggesting a significant level of variation in company size.

Table 4. Descriptive statistics of the samples

Variable name	Sample size	Mean value	Standard deviation	Minimum value	Maximum value
|CAR(–3,3)|	335	0.0795	0.0864	0.0000	0.5371
Score	335	0.7147	0.2112	0.0000	1.0000
Size	335	21.3877	4.4874	0.0000	28.5920
Asset	335	23.0151	1.8227	19.4464	30.0413
Roe	335	0.0497	0.4142	–3.5279	5.3159
TobinQ	335	2.2255	2.3309	0.0000	22.3205
Debt	335	0.4627	0.2175	0.0317	0.9747
Insv	335	0.04831	0.2467	0.0000	1.5212

4.3.2. Regression analysis of clarification announcement sentiment level and clarification effect under different rumor nature

Table 5 displays the results of the fixed effects regression model. Initially, we perform a baseline regression analysis on the entire sample. The table's first column reveals that the

Table 5. Results of regression analysis of the sentiment of clarification announcements and the effect of clarification

Variables	Overall	Positive rumors	Negative rumors	Neutral rumors
	|CAR (–3,3)|	|CAR (–3,3)|	|CAR (–3,3)|	|CAR (–3,3)|
Score	0.0625***	0.0906*	0.0396*	0.0213
	(2.80)	(1.84)	(1.69)	(0.21)
Size	–0.0009	0.0005	–0.0010	0.0001
	(–0.88)	(0.17)	(–0.91)	(0.03)
Debt	0.0211	0.0868	0.0258	–0.0008
	(0.78)	(1.38)	(0.93)	(–0.01)
Roe	–0.0174	0.0187	–0.0134	–0.1773*
	(–1.54)	(0.22)	(–1.42)	(–1.71)
TobinQ	0.0037*	0.0048	0.0053**	0.0058
	(1.75)	(0.80)	(2.06)	(1.13)
Insv	–0.0212	0.0405	–0.0137	–0.0665
	(–0.95)	(0.94)	(–0.56)	(–0.82)
Asset	–0.0084**	–0.0188**	–0.0047	–0.0064
	(–2.34)	(–2.38)	(–1.23)	(–0.48)
Constant	0.2398***	0.3719**	0.1544*	0.2543
	(3.11)	(2.22)	(1.78)	(0.93)
N	335	87	179	69
r2_a	0.0594	0.0418	0.0333	0.0287

Note: t statistics in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

explanatory variable, the positive sentiment score of clarification announcements, has a coefficient of 0.0625 at a significance level of 1%. This suggests that as the positive sentiments expressed in clarification announcements increase, so does the absolute value of cumulative abnormal returns. In other words, clarification announcements improve the effectiveness of clarifying the situation. The use of positive language and tone in clarification announcements could potentially improve the company's reputation and bolster investors' confidence in the content of such announcements, thereby reducing abnormal stock volatility. Moreover, the control variables reveal a significantly negative coefficient for the total firm assets, indicating a greater susceptibility of larger listed companies to rumors and a diminished effectiveness of clarification statements. Tobin's Q value shows a significant positive correlation, implying that rumors have less impact on companies with higher market capitalization and they gain more from clarification announcements.

The last three columns of Table 5 present the results of the subgroup regressions, grouped by the nature of the rumor. At a 10% level of significance, the regression analysis reveals that the outcomes for both positive and negative rumors are significantly positive. This suggests that the positive mood expressed in clarification announcements effectively clarifies both positive and negative rumors. The coefficient for the positive sentiment score of clarification announcements regarding positive rumors is 0.0906, which is greater than the coefficient for the positive sentiment score of clarification announcements regarding negative rumors, which is 0.0396. This suggests that the positive sentiment factor of clarification announcements has a more pronounced impact on the clarification effect in positive rumors. Nevertheless, the coefficients of the explanatory factors in the neutral rumor group exhibit positive values, but they lack statistical significance. As a result, there is no discernible relationship between the positive emotion conveyed in clarification announcements and the efficacy of clarifying neutral rumors.

Therefore, we may infer that the optimistic tone of clarification announcements improves their clarity, especially when favorable rumors are involved. Therefore, Hypothesis H3 has been confirmed. The disparity may stem from the fact that favorable rumors contribute to a positive perception of the company, bolstering investors' confidence in both the company itself and the accuracy of its clarification statements. Moreover, the inclusion of positive language and tone in these statements serves to solidify this trust, thereby amplifying the effectiveness of the clarification announcements.

4.3.3. Regression analysis of affective level of clarification announcement and clarification effect under different corporate information transparency

Columns 2 and 3 of Table 6 present the findings of the regressions for subgroups with varying levels of corporate information transparency. The findings for the high firm information transparency group indicate that the coefficient on the positive sentiment score for clarification announcements is 0.0831, with a significance level of 1%. This suggests that the impact of clarification announcements on sentiment is more noticeable when firms have a high level of information transparency. In comparison to the entire sample (Table 5), the adjusted R2 of the model for the high corporate information openness group is also significantly higher, indicating a more accurate fit for the same model. Nevertheless, the explanatory variables' coefficients for the group with low corporate information transparency are positive but not statistically significant. Therefore, when corporate information transparency is low, there is no significant correlation between the degree of sentiment toward clarification announcements and the clarification effect. Consequently, there is a notable disparity in the emotional impact of clarification announcements between the high and low corporate information transparency groups. Furthermore, the emotional impact of clarification announcements is more pronounced in the high corporate information transparency group compared to the low corporate information transparency group.

4.3.4. Regression analysis of affective level of clarification announcement and clarification effect of different firm natures

The final two columns of Table 6 present the outcomes of the regressions for subgroups with distinct firm characteristics. The regression analysis reveals that the coefficient of the positive sentiment score for clarification announcements in the non-SOEs group is 0.0673, with a significance level of 5%. This suggests that the impact of clarification announcements on sentiment is more pronounced when the firm is not a state-owned enterprise. Nevertheless, the coefficient of the explanatory factors in the SOEs group is positive but lacks statistical significance. Therefore, there is no substantial association between the level of sentiment in clarification announcements and the effectiveness of clarification when the firm is a state-owned enterprise. Hence, there exists a notable distinction between the SOEs and non-SOEs groups, and the impact of clarifying statements on emotions is more pronounced in the non-SOEs group as opposed to the SOEs group.

Table 6. Results of the heterogeneity analysis of clarifying announcement sentiment and clarifying effect

	High information transparency	Low information transparency	SOEs	Non-SOEs
	|CAR (–3,3)|	|CAR (–3,3)|	|CAR (–3,3)|	|CAR (–3,3)|
Score	0.0831***	0.0252	0.0500	0.0673**
	(3.33)	(0.50)	(1.29)	(2.45)
Size	–0.0007	–0.0025	–0.0009	–0.0011
	(–0.67)	(–0.63)	(–0.54)	(–0.84)
Debt	0.0832**	–0.0690	–0.0007	0.0277
	(2.38)	(–1.39)	(–0.01)	(0.87)
Roe	0.0159	–0.0139	0.0113	–0.0194
	(0.43)	(–1.02)	(0.24)	(–1.62)
TobinQ	0.0044*	0.0028	–0.0062	0.0043*
	(1.93)	(0.50)	(–0.66)	(1.95)
Insv	–0.0160	–0.0217	0.0215	–0.0340
	(–0.66)	(–0.40)	(0.39)	(–1.30)
Asset	–0.0139***	0.0041	–0.0131*	–0.0082*
	(–3.29)	(0.44)	(–1.78)	(–1.87)
Constant	0.3117***	0.0721	0.3637**	0.2366**
	(3.56)	(0.37)	(2.42)	(2.44)
N	234	101	84	251
r2_a	0.0940	–0.0163	0.0103	0.0495

Note: t statistics in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.4. Robustness testing

This research examines the robustness of the regression results using two approaches. The initial approach involves prolonging the estimation period in the event study method by extending the original estimation period [TC-160, TC-10] to [TC-210, TC-10]. The outcomes are displayed in column (1) of Table 7, where the sentiment score coefficient for the entire sample group is determined to be 0.0613, with a significance level of 1%. This suggests that

Table 7. Robustness test results

	(1)	(2)
	|CAR (–3,3)|	|CAR (–3,3)|
Score	0.0613***	0.0821**
	(2.75)	(2.43)
Size	–0.0011	–0.0008
	(–1.05)	(–0.65)
Debt	0.0154	0.0104
	(0.57)	(0.30)

End of Table 7

	(1)	(2)
	|CAR (–3,3)|	|CAR (–3,3)|
Roe	–0.0161	-0.0273^{*}
	(–1.43)	(–1.74)
TobinQ	0.0034	0.0025
	(1.62)	(1.01)
Insv	–0.0211	–0.0274
	(–0.95)	(–0.91)
Asset	-0.0087^{**}	-0.0102^{**}
	(–2.42)	(–2.27)
Constant	0.2547^{***}	0.2832^{***}
	(3.31)	(2.86)
N	335	227
r2_a	0.0622	0.0707

Note: t statistics in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

the study's findings are resilient. The second approach involves modifying the sample size by decreasing it from 335 to 227. We achieve this reduction by reducing the sample period to four years, specifically from 2020 to 2023. The collected findings are displayed in column (2) of Table 7. The table results indicate that the sentiment score coefficient is 0.0821, which is statistically significant at a 5% level. This suggests that the conclusions of this research are reliable and strong.

5. Conclusions and limitations

This study examines 335 instances of rumor clarifications in China's A-share market from 2019 to 2023. It investigates the impact of clarification announcements made by listed companies and analyzes the influence of sentiment factors using various methods, including text sentiment analysis, event study analysis, and fixed-effects regression modeling. We can summarize the findings of this research article as follows: (1) Market rumors induce anomalous volatility in stock values, with the impact varying depending on the nature of the rumors. Positive and neutral rumors lead to upward deviations in stock prices, whereas negative rumors result in downward deviations. (2) The issuance of clarification statements leads to a restoration of stock prices. However, the impact of clarifying rumors of different types varies. Specifically, the clarification of positive rumors has the most favorable effect, while the clarification of negative rumors lacks market efficacy. (3) The efficacy of clarification announcements is influenced by their emotional aspects. Positive emotions increase the efficacy of clarification statements, and this impact is particularly strong when addressing positive rumors. (4) The emotional impact of clarification statements is determined by the level of transparency in company information. Greater transparency of business information leads to a stronger impact of positive emotions on clarification announcements, while lesser transparency results in a weaker influence of positive emotions on clarification announcements. (5) The emotional impact of a clarifying statement is influenced by the characteristics of businesses. A clarification statement's attitude has a significant impact on its effectiveness for non-state-owned firms, but for state-owned enterprises, the impact is quite minimal.

In conclusion, we recommend the implementation of the following measures: Initially, publicly traded firms address rumors by making clarification announcements. When firms encounter positive rumors, they may employ emotional tactics, such as using positive language in the clarifying statement, to amplify the impact of the announcement. When confronted with negative and neutral rumors, enterprises should exercise caution and employ appropriate strategies to appeal to emotions. They should strive to disclose the actual situation in an objective and truthful manner. It is important to note that appealing to emotions may have a limited impact initially, but it will not be effective in achieving long-term clarification effects. Furthermore, businesses are able to improve communication effectiveness by increasing the level of transparency in their corporate information.

This paper has two specific shortcomings: First, it's important to acknowledge that the timing of rumors in this article's sample might be imprecise. The announcement only includes a few rumors, while the rest are obtained through the process of locating and filtering rumor news or by loosely counting within the first 0–3 days of the clarification statement. This uncertainty in timing may affect the precise capture of rumor propagation dynamics and its impact, thereby somewhat weakening the timeliness and accuracy of the research conclusions. Furthermore, the sentiment score of the clarification announcement was assessed using the sentiment lexicon provided by GooSeeker sentiment evaluation. However, it's crucial to understand that the sentiment dictionary we used is neither authoritative nor representative. The text's sentiment grading will contain some bias, which could stem from factors such as limitations in lexicon construction, preferences in vocabulary selection, and the granularity of sentiment classification. This potential bias may not only hinder the accurate judgment of rumor sentiment tendency but may also further interfere with the in-depth analysis of rumor propagation effects and public reactions.

The findings of this study have significant theoretical and practical value for business management and rumor governance. Furthermore, they extend the scope of existing research on rumor governance. In light of these findings, future research could focus on two distinct yet interrelated areas. The first is the refinement of rumor governance. Future research may formulate strategies based on rumor types, content, and dissemination characteristics, and explore the role of the media, especially in guiding public sentiment and effectively disseminating true information. The second area of future research is to examine the current dilemma of negative rumor governance, propose solutions, and use advanced technical means to improve the efficiency of identification, monitoring, and response. At the same time, analyze its impact on social trust, and restore and enhance public trust through transparent disclosure, public relations strategies, and trust-building activities. Moreover, future research can delve deeper into how different emotional tones in announcements specifically influence investor behavior, in order to gain a more comprehensive understanding of the mechanism by which emotions operate in financial markets.

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Conflict of interest

There is no conflicts of interest for any author in this manuscript.

Disclosure statement

All authors approve the manuscript and give their consent for submission and publication.

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