Rumor and Clarification:

Abnormal Volatility in the Chinese Stock Market *

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Abstract

This study examines the impact of rumors and clarifications on stock volatility in the Chinese stock market, focusing on the shift from information asymmetry to transparency in information dissemination. Utilizing a novel dual-event study to measure abnormal volatility, it disentangles the distinct effects of rumors and clarifications on stock price fluctuations. The findings reveal that rumors significantly drive abnormal volatility as investors react to unverified information, while clarification announcements also induce volatility as markets process verified information. Although volatility gradually subsides following clarifications, their stabilizing effects remain limited. This pattern is robust across parametric, nonparametric, and bootstrap analyses, confirming that clarifications mitigate but do not eliminate rumor-induced volatility. Regression analysis indicates that positive rumors, particularly those originating from social media or involving state-owned enterprises, are less likely to be true. Moreover, positive rumors tend to generate higher abnormal volatility compared to negative rumors. This contradicts prior studies suggesting a stronger impact of negative news. The study contributes to the literature by integrating theoretical frameworks, demonstrating the role of regulatory interventions, and providing insights into market stability in emerging economies.

Keywords: Rumors, Clarifications, Stock Volatility, Market Efficiency, Event Study.

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1. Introduction

Information drives stock price fluctuations by facilitating investors' evaluation of a firm's intrinsic value (Fama, 1970). Rumors, as a form of unverified information, are speculative by nature and intensify uncertainty surrounding a firm's fundamentals, thereby amplifying market volatility. In contrast, clarification announcements aim to reduce this uncertainty by providing accurate and verifiable information, stabilizing market perceptions. Nevertheless, when clarifications fail to fully mitigate the effects of rumors, questions arise about the efficiency of the market in processing information. This study investigates the role of information accuracy (i.e., misinformation and truth) in shaping stock price fluctuations over time.

We examine how changes in information quality influence abnormal volatility, focusing on the role of rumors and clarification announcements in the Chinese stock market. Three factors make the Chinese market crucial for studying this issue. First, the media's tendency to publish sensational and unverified stories presents a significant concern (Ahern and Sosyura, 2015), and China's mandatory clarification policy provides a unique framework to analyse the market impact of rumors and the effectiveness of clarifications, which is difficult in markets lacking such regulations. Second, despite being the world's second-largest market by capitalization, China's stock market remains underdeveloped, with limited transparency and restricted access to reliable information (Liang et al., 2020). This lack of transparency makes it difficult for investors to verify rumors, causing unverified information to have a stronger influence on stock prices than fundamental data. Third, the market is heavily dominated by retail investors, who account for approximately 85% of trading volume (Jones et al., 2021; Liu et al., 2016). These investors often lack sophisticated financial skills, engage in speculative trading, and react sharply to unverified information, thereby amplifying price fluctuations (Bailey et al., 2009; Xiong & Yu, 2011).

Progress in measuring the impact of rumor-related issues has been limited, as existing studies often face conceptual and empirical challenges. For instance, Hirshleifer et al. (1994), Van Bommel (2003), and Brunnermeier (2005) develop theoretical models to explain market phenomena like "buy the rumor, sell the news," offering valuable insights but lacking direct empirical validation. On the empirical side, Kadan et al. (2018) use analyst forecast changes as proxies for rumors, but their approach struggles to distinguish between unverified rumors and leaked information, complicating the isolation of rumors' effects. Ahern & Sosyura (2015) provide more targeted evidence by studying takeover rumors, showing that uninformed investors overreact to sensational news. While these studies highlight progress, they underscore the ongoing difficulty in accurately capturing and quantifying the market impact of rumors.

This study leverages clarification announcements mandated by Chinese regulatory authorities to provide a reliable basis for identifying rumors and analyzing their market impact.[3] Using a modified dual-event study methodology, it disentangles the effects of rumors and clarifications on stock price fluctuations. This approach enhances data reliability and methodological rigor, advancing the empirical understanding of stock market dynamics driven by rumors and clarifications.

We begin with 3,515 clarification announcements manually extracted from the Shanghai and Shenzhen Stock Exchanges, covering the period from January 30, 2007, to December 31, 2022. These announcements are utilized to identify related rumors, with each rumor-clarification pair categorized by tone and accuracy as True Positive, True Negative, False Positive, or False Negative. To ensure classification accuracy, an independent research assistant verifies the categorizations. Furthermore, we validate the tone assessment by

[3] Company-identified rumors may present endogeneity issue, as firms might prioritize clarifying false negative rumors over false positive ones to serve their own interests. However, due to monitoring by the China Securities Regulatory Commission (CSRC) and legal requirements, such bias is unlikely. Companies face legal consequences for unaddressed rumors.

analyzing stock price reactions around rumor releases, calculating the average abnormal returns for each category. The alignment of positive (negative) tones with positive (negative) abnormal returns provides evidence supporting the validity of the tone classification (see Supplement Appendix D1). This process yields 2,229 rumor-clarification pairs for summary statistics, enabling an analysis of their characteristics. Our findings indicate that negative rumors dominate the Chinese stock market, with approximately 85% of rumors classified as false. For the final analysis, 2,127 pairs from 1,376 unique stocks are included to meet the methodological requirements for estimation.

We employ a modified dual event study methodology to evaluate the impact of rumors on abnormal volatility in the Chinese stock market and the role of clarifications in reducing market uncertainty. To ensure precision, we identify the initial articles reporting each rumor and record the timing of both rumor releases and corresponding clarifications. As shown in Figure 1, this approach tracks stock price volatility around these events. Our findings reveal that rumors significantly increase abnormal volatility, with effects peaking on the rumor release day. Clarifications, by providing true disclosures, help reduce uncertainty and guide the market toward stability. Specifically, abnormal volatility subsides within three days for most rumors, except for false positives, where the stabilization process takes approximately 26 days.[4]

Next, we use quadratic volatility analysis and the bootstrap approach to improve the reliability of measuring abnormal volatility. Our findings confirm that abnormal volatility is concentrated around rumor and clarification phases, with clarifications gradually help to reduce

[4] Our analysis assumes that rumors drive market movements, but it is possible that market movements influence news instead (Engelberg & Parsons, 2011). While we cannot fully rule out this possibility, we partially address reverse causality by extending the pre-event window to 60 days to check for spikes prior to the rumor release date (see Supplement Appendix D2). If the highest spikes occur near or on the rumor release day, it is unlikely that market movements drive news.

uncertainty. Thus, these additional tests provide robust evidence for assessing abnormal volatility, an underexplored metric in existing literature.

We apply a logistic regression to investigate whether the truthfulness of a rumor can be predicted (i.e., its likelihood of materializing). Larger companies, firms in highly regulated environments (e.g., State-Owned Enterprises [SOEs]), and those frequently covered in the media may have greater resources to manage misinformation and stricter requirements for accurate disclosure. Therefore, these firms are expected to have a positive association with rumor truthfulness. However, our results indicate that positive rumors originating from social media are less likely to be true, supporting previous findings that social media often serves as a 'rumor mill' (Jia et al., 2020). Similarly, positive rumors about SOE firms are also less likely to be true, possibly reflecting that investors' trust in SOEs makes them prime targets for positive rumors.

We further examine the determinants of abnormal volatility during different stages of the rumor clarification process. This analysis aims to identify the factors driving abnormal volatility and evaluate whether clarifications effectively manage market uncertainty. We find that positive (negative) rumors about SOEs are associated with higher (lower) volatility. This indicates that investors are more likely to believe positive rumors and exhibit less concern about negative ones for SOEs. Besides, we find that positive rumors, in general, induce consistently higher volatility, challenging existing literature that emphasizes stronger reactions to negative news (e.g., Badshah et al., 2018; Bekiros et al., 2017). This pattern suggests that opportunistic traders may exploit positive rumors to create market disruptions. In addition, we observe a continuation effect, where previous periods of abnormal volatility are positively associated with subsequent volatility, underscoring the persistence of market uncertainty during the rumor clarification process. Interestingly, the veracity of rumors (true or false) and the timing of clarifications (timely or delayed) do not significantly affect abnormal volatility.

These findings suggest that while clarifications aim to provide transparency, their ability to stabilize market fluctuations is limited.

This paper makes several contributions to the literature on financial market dynamics and information dissemination. First, it provides a detailed empirical analysis of the distinct impacts of rumors and clarifications on stock volatility in China's emerging markets, advancing our understanding of how the changes of information shapes investor. Second, the paper introduces a novel dual-event study methodology, incorporating two consecutive event windows to capture market reactions to rumors and clarifications more precisely. Unlike prior studies relying on broad information proxies such as announcement effects (Mitchell and Mulherin, 1994) or media prominence (Klibanoff, Lamont, and Wizman, 1998), this approach enables a more accurate assessment of the specific impacts of informational events on stock volatility. Third, this study integrates key theoretical frameworks from Diamond (1985), Diamond and Verrecchia (1991), Dye (1985), Lewellen and Shanken (2002), and Pastor and Veronesi (2003) to examine how corporate and regulatory interventions influence market volatility. This linkage between theoretical models and empirical analysis enriches the literature on rumor-driven volatility and market stabilization. Fourth, the study examines China's unique clarification policies, highlighting how regulatory interventions influence market stability in emerging markets, with implications extending to developed markets. Finally, the paper challenges conventional findings by demonstrating that positive rumors, rather than negative ones, have a stronger impact on stock volatility. This finding contrasts with existing studies emphasizing stronger reactions to negative news (e.g., Badshah, Frijns, and Tourani-Rad, 2018; Bekiros, Nguyen, and Uddin, 2017; Tetlock, 2007) and suggests that market participants may exploit positive rumors to disrupt the market.

The rest of the paper is organized as follows. Section 2 discusses the investor base and clarification legislation in China. Hypotheses regarding rumors-clarification are also developed in the context of China stock market. Section 3 presents the data collection process and analyses the rumor-clarification data. Section 4 describes the methodology employed in the study. Section 5 examines the main findings, while Section 6 addresses the robustness of the results. Section 7 concludes the paper.

2. Related Literature and Hypothesis Development

2.1 Institutional Background

2.1.1 Individual Investors in the China Stock Markets

Rumors play a significant role in shaping investor behavior, particularly in markets dominated by individual investors. It refers to unverified and widely disseminated information that circulates among individuals or groups, often influencing investor behavior and prompting potentially irrational, emotion-driven trading decisions (Allcott & Gentzkow, 2017; Kimmel, 2004). The Chinese stock market is uniquely characterized by the dominance of individual investors, who are pivotal in both participation and trading volume, distinguishing it from markets predominantly influenced by institutional investors. Retail investors in China, contributing to approximately 85% of trades, play a critical role in shaping market dynamics, yet are often considered to have limited sophistication and information processing capabilities (Tian et al., 2018; Titman et al., 2021; Wan et al., 2016). This investor profile, combined with the speculative nature of the market, significantly increases the market's vulnerability to rumors, leading to pronounced price fluctuations.

The rapid dissemination of information, both accurate and misleading, through social media platforms in the digital era, poses substantial challenges in maintaining market stability. This scenario is further complicated by the speculative trading behaviors of retail investors, who frequently base their decisions on unverified information, thus deviating from fundamental stock values and contributing to increased market volatility (Tetlock, 2007).

Moreover, the Chinese stock market is plagued by the widespread belief among investors in the existence of information leakage and insider transactions, which fuels reliance on rumors for investment decisions and further destabilizes the market (Hamilton & Lin, 1996). The challenges in enforcing regulations against rumor-mongering are exacerbated by limited administrative resources and the difficulty in tracing the origins of rumors, resulting in minimal legal risks for those spreading misinformation.

This environment not only fosters fertile ground for speculators, opportunists, and media to create and spread sensational rumors for profit but also underscores the significant susceptibility of the Chinese stock market to rumors. Such dynamics underscore the urgent need for enhanced regulatory measures and investor education to mitigate the adverse impacts of rumors on market stability and investor trust.

2.1.2 Anti-Rumors and China Legislation

Regulators need to deploy state-of-the-art technology to identify trading patterns indicative of rumor-fueled activities (Putniņš, 2012) and to counter these rumors with full and accurate information (Wen et al., 2014). Strict legal penalties for spreading false rumors are essential to prevent deceptive practices (Engelen & Van Liedekerke, 2007).

Corporations must communicate openly to counter the harmful effects of rumors (Kimmel, 2004), swiftly addressing false or inaccurate claims through established channels (Bordia et al., 2005; Difonzo, 2000). Investors should diligently evaluate rumors and authenticate information prior to executing trades, thereby avoiding rash decisions based on speculative information (Koriat et al., 2000).

Media organizations are expected to adhere to journalistic ethics by verifying financial information prior to its dissemination (Ahern & Sosyura, 2015) and to prioritize balanced reporting over sensationalism (Allcott & Gentzkow, 2017). The monitoring of online discussions and active engagement with digital communities to refute rumors are also deemed essential (Jia et al., 2017).

Addressing rumors at their source and providing factual and detailed information is a direct and effective strategy for companies to neutralize them (Wen et al., 2014). Clarifications aim to mitigate rumor impacts by ensuring accurate information, crucial for maintaining market integrity and investor protection (Engelen & Van Liedekerke, 2007). These announcements help reduce information asymmetry, decreasing the likelihood of certain investors capitalizing on rumors to influence the market (Milgrom & Stokey, 1982) and stabilizing prices (Ahern & Sosyura, 2015). Additionally, they protect companies' reputations from harmful rumors, thereby avoiding reputational damage and curbing investor herd behavior that can lead to market reactions (Bordia et al., 2005; Van Bommel, 2003). Since the Securities Law in 1998, China has set basic corporate disclosure requirements, enhanced through amendments. However, initial legal inadequacies and lack of specific measures led to low costs for errors, making disclosure and clarification requirements relatively voluntary.

On 13 December 2006, the China Securities Regulatory Commission (CSRC) passed the "Measures for Administrating the Information Disclosure of Listed Companies (No.40)," which mandates that all listed companies disclose information equitably, especially news circulated in public media that could significantly impact stock prices. This regulation took effect on 30 January 2007.[5] This regulation requires companies involved in rumors or information leaks to issue timely clarification announcements through CSRC-designated media. Rumors are difficult to quantify, but they must meet three criteria under the regulation to be considered a rumor: they must be unverified information, widely spread through public channels, and have a potential or actual significant impact on stock prices. To clarify a rumor, a company must detail the rumor's specifics, the factual circumstances surrounding it, and any additional clarifying information. Corporate boards face strict accountability for non-compliance with clarification obligations, with penalties determined by the severity of the

[5] This requirement is available in Chinese on the official government website http://www.csrc.gov.cn/csrc/c101864/c1024663/content.shtml.

breach, ranging from public reprimands and fines to legal sanctions and market bans (CSRC, 2006). This regulatory framework mandates companies to proactively manage rumors. Consequently, firms must either refute false rumors or explain why certain information has not been disclosed.

2.2 Hypothesis Development

2.2.1 Rumors Effect on Stock Volatility

The Efficient Market Hypothesis (EMH) posits that stock prices should instantly reflect all available information, assuming market participants act on factual and verifiable data, but investor behavior often diverges from this ideal (Fama, 1970). Empirical studies and theoretical analyses show that rumors can trigger significant market reactions, leading to abnormal fluctuations in stock prices (Diamond & Verrecchia, 1981; Shleifer & Summers, 1990). Bailey et al. (2006) and Cready & Hurtt (2002) demonstrate that abnormal volatility effectively captures investors' responses to information events. The theory of information asymmetry suggests that disparities in information access among market participants is related to inefficiencies such as stock price volatility (Akerlof, 1970). Rumors, as a form of uncertainty, exacerbate this by giving some individuals knowledge about their truthfulness, further increasing volatility (O'Hara & Easley, 2004).

Despite the inherent uncertainty of rumors, investors' reactions are often influenced by the psychological and social forces at play, with the perceived credibility of the source and the historical accuracy of rumors affecting their responses (Bordia et al., 2005; Difonzo, 2000; Peterson & Gist, 1951). In a market governed by rational expectations, investors would theoretically discount rumors, prioritizing tangible, verifiable information over speculative hearsay (Fama, 1970). However, because markets and investors can be irrational, psychological and social factors still play a significant role. Under conditions of information asymmetry, these psychological factors and heuristic-driven decision-making significantly influence investor behavior (Kahneman & Jenkins, 1974). Additionally, the correlation between rumors spread through social media platforms and stock market movements underscores the powerful impact of speculative information on market dynamics (Bollen et al., 2011).

The dissemination of rumors in the stock market can undermine investor confidence and market stability (Zivney et al., 1996). Negative rumors, in particular, can significantly damage a company's public image and are sometimes used strategically for personal gain, raising ethical and integrity concerns within financial markets (Atanasov et al., 2015; Engelen & Van Liedekerke, 2007; Putniņš, 2012). Such dynamics exacerbate information asymmetry, leading to market inefficiencies where stock prices do not accurately reflect the underlying value of assets (Kimmel, 2004; Fama, 1970).

The unique characteristics of the Chinese stock market, particularly the prevalence of retail investors with varying financial literacy and a tendency for speculative trading based on rumors, add complexity to information dissemination and market reactions. Unverified information can significantly influence investor behavior and stock prices, highlighting the nuanced interplay between market efficiency, investor psychology, and the impact of rumors. This environment challenges the EMH's notion of rational decision-making, suggesting that rumors should have minimal impact on stock price volatility, as stock prices already incorporate all available information, rendering rumors redundant (Fama, 1970).

Considering these aspects, we propose our first null hypothesis:

H1: Rumors do not significantly impact stock price volatility in the Chinese stock market.

2.2.2 Clarification Announcements Effect on Stock Price Volatility

Clarification announcements are strategic tools used by corporations to mitigate the impacts of rumors and misinformation by disseminating accurate information to the market.

These announcements are designed to decrease uncertainty and, as a result, market volatility. Heflin, Subramanyam, and Zhang (2003) have shown that timely and transparent disclosures are related to reduced stock price volatility in a long time, emphasizing the stabilizing influence of clear information. Clarification announcements serve as a signaling mechanism to correct misinformation induced by rumors because they provide accurate information that reduces uncertainty. According to signaling theory from Spence (1973) such announcements signal the company's transparency and reliability. Ross (1977) notes that credible information releases can significantly alter investors' perceptions and expectations, thereby stabilizing stock prices. By directly addressing rumors with factual information, clarification announcements help restore market confidence and correct any misinformation.

The effectiveness of these announcements in curbing volatility triggered by rumors depends on factors such as investor psychology, market dynamics, and the specifics of the clarifications (Amihud & Mendelson, 1986; Yang & Luo, 2014). Factual disclosures can significantly reduce market uncertainty and misinformation, aligning investors' expectations and stabilizing stock prices (Barry & Brown, 1985; Welch, 1989). However, if the clarification process is inefficient, it may further amplify volatility. The impact on post-rumor stock price volatility varies based on the nature of the rumors, the timing and content of the announcements, and prevailing market conditions. For instance, timely clarifications are crucial; delays can allow rumors to further impact market sentiment and prices, reducing the effectiveness of the announcements (Yang & Luo, 2014).

Clarification announcements in financial markets face challenges due to cognitive bias, misinformation, and the rapid spread of rumors, affecting their effectiveness in stabilizing stock prices. Market participants' diverse interpretations and actions, influenced by cognitive biases such as confirmation bias, mean that clarifications can have varied effects on stock price volatility (Koriat et al., 2000; Milgrom & Stokey, 1982). Initial rumors may continue to influence stock prices and trading volumes due to overreactions and the ongoing spread of misinformation by those seeking short-term gains (Başci et al., 1996; Spiegel et al., 2010). The complexity of financial information and the rapid dissemination of rumors through social media further complicate the immediate impact of clarifications, allowing rumors to persist despite countermeasures (Allcott & Gentzkow, 2017; Lewandowsky et al., 2005). Conversely, the EMH posits that clarification announcements have limited influence on stock prices because all available information is already reflected in the prices, making such clarification redundant (Fama, 1970).

Given these considerations, our second null hypothesis is:

H2: Clarification announcements do not significantly impact stock price volatility following rumors.

2.2.3 Predict the Veracity of Rumors

We investigate whether the veracity of rumors can be predicted. Firm fundamentals, including earnings, revenue growth, debt levels, and other indicators of financial health, are conventionally regarded as pivotal determinants of a company's intrinsic value (Fama & French, 1992). However, the connection between these fundamentals and the accuracy of market rumors is complex. Robust fundamentals may suggest a company's strength, but they do not necessarily guarantee the truthfulness of prevalent market rumors (Shleifer & Vishny, 1997). This discrepancy is attributed to the speculative nature of rumors, which may not accurately reflect the firm's true economic conditions (Kyle & Viswanathan, 2008).

The rapid spread of information and misinformation via digital platforms complicates the task of distinguishing between fact-based forecasts and speculation (Bollen, Mao, & Zeng, 2011). Tetlock (2007) indicates that media content significantly impacts investor sentiment and market outcomes, amplifying the influence of rumors.

The ownership structure of the companies, particularly SOEs, can influence the truthfulness of rumors. SOEs operate under different motivations and constraints compared to privately-owned firms, including political and social objectives (Megginson & Netter, 2001). Their close ties with government entities are related to politically motivated news or those aimed at influencing public perception and policy (Borisova et al., 2012). Consequently, investors may place more trust in government-affiliated companies, making SOEs more attractive targets for speculators.

Behavioural finance literature suggests that investor psychology and sentiment profoundly influence the stock market, often resulting in irrational trading behaviours that deviate from firm fundamentals (Shiller, 2003). Das & Chen (2007) highlight the importance of sentiment analysis in social media to gauge investor mood and its potential impact on market behaviour. Similarly, Barberis et al. (1998) show that psychological factors such as overreaction and underreaction to news can create market anomalies, disrupting the expected relationship between firm performance and stock prices.

These factors magnify the effects of rumors regardless of the firm's actual financial performance. This suggests that firm fundamentals and the related variables are insufficient for reliably predicting the accuracy of rumors (Daniel et al., 1998).

H3: The veracity (True or False) of rumors cannot be predicted.

2.2.4 Determinants of Rumors and Clarification Effects on Stock

We further explore the complex interplay of factors influencing the impact of rumors and clarifications on stock volatility. SOEs play a crucial role in China's economy, acting as key instruments for governmental economic and social policies (Kang, 2021). Their unique governance structure, marked by government influence over CEO appointments and compensation, increases information asymmetry and obscures true performance. However, SOEs benefit from government support and preferential access to resources, which enhances positive news and investor perceptions.

The advent of social media has revolutionized information dissemination, enabling the rapid spread of both accurate information and rumors (Jia et al., 2020). Social media platforms facilitate a cascading effect where rumors gain undue credibility through repeated sharing. This, combined with the low barrier to content creation, highlights social media's dual role as both an aggregator of information and a potential source of market distortion. The persuasion bias on social media can lead investors to overestimate the credibility of rumors, significantly influencing stock volatility. Tetlock (2007) and Da et al., (2015) demonstrate the impact of media sentiment and investor attention on stock price movements, indicating that both the tone and volume of information can amplify market volatility.

Short selling constraints limit investors' ability to trade on negative information, leading to the systematic overvaluation of securities (Diamond & Verrecchia, 1987; Miller, 1977). Despite recent regulatory changes in China aimed at easing these constraints, the market still struggles to efficiently incorporate negative information (Bris et al., 2007). The restricted ability to short sell in response to rumors or clarifications can exacerbate volatility, affecting price stability and informational efficiency.

H4: No factor significantly influences the impact of rumor and clarification on stock price volatility.

3. Data

We investigate the effect of rumors, and their subsequent clarifications of A-share stocks listed in the Chinese Stock Exchanges, i.e., Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). The sample period is from 30 January 2007 to 30 December

2022. The dataset is comprised of several data sources including manually collected rumor-clarification data, and firms' characteristic data.

3.1 Rumors and Clarification Data

Without accurate event dates, any analysis is flawed. For this reason, we spend considerable effort investigating methods to obtain accurate rumor and clarification dates. We use manually collected data rather than the data from the Chinese Research Data Services (CNRDS) database because we find numerous inaccuracies in this database.[6]

We extract clarification announcements from the official websites of the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). These announcements include the company name, stock code, announcement date and time, a brief summary of the relevant rumor, the rumor's source, and whether the rumor is true (e.g., information leakage) or false (e.g., fake news). For a detailed example, see the clarification announcement in Appendix B1. This information enables us to manually search for the related rumor for the corresponding stock.

Table 1 summarises the filtering steps to obtain our rumor-clarification pairs. Starting with 3,515 clarification announcements from 2007 to 2022, we manually matching them with corresponding rumors. The sample selection process involves several steps: 1) Excluding pairs no longer available online;[7] 2) Removing clarifications from the same stock within a 120-day

[6] Accurate event dates are crucial for event studies to determine the true impact of events on stock price fluctuations. Previous literature has used data from the Chinese Research Data Services (CNRDS), which is less accurate. For example, Wu list two examples, i.e., Jiugui liquor rumor clarified as false on 24th December 2019, and the Gotion High-Tech rumor confirmed as true on 17th January 2020 (see page 5, footnote 5). However, our evaluation reveals the actual clarification date for Jiugui liquor was 22nd December 2019 and it's a non-trading day, making the effective date 23rd December 2019, the subsequent trading day (http://vip.stock.finance.sina.com.cn/corp/view/vCB_AllBulletinDetail.php?gather=1&id=5818651). Conversely, the Gotion High-Tech rumor was accurately clarified on 20th December 2020, not 17th January as recorded by CNRDS (http://vip.stock.finance.sina.com.cn/corp/view/vCB_AllBulletinDetail.php?stockid=002074&id=5870616).

[7] The reason that we cannot find the corresponding rumor may be due to: (1). the clarification announcement has incomplete and vague information. (2). The rumor was removed from the relevant news and social media platforms.

period to avoid overlapping effects;[8] 3) Discarding pairs released on the same trading day; 4) Deleting rumors and clarifications during stock trading halts;[9] and 5) Excluding neutral rumors. These criteria resulted in 2,229 valid pairs for summary statistics. For our event study, we required a minimum of 120+10 (estimation period + private rumor period) trading days before the event and a 60-day post-event window to calculate abnormal and cumulative abnormal volatility. The final sample for our analysis comprised 2,127 rumor-clarification pairs involving 1,376 unique stocks.

Appendix A details the release times for both rumors and clarifications. In Appendix A1, we define the effective date used to measure the impact of rumor clarifications. The following charts illustrate distinct timing patterns for the release of rumors and their subsequent clarifications. Figure A2 presents the frequence of rumor release during different time throughout the day. The blue bars represent the probability of rumors being released at each hour, while the yellow sections highlight the official trading hours of Chinese stock exchanges. We find that rumors are typically disseminated in the morning before market opening and are least active after market closing.[10] Figure A3 indicates that the majority of rumors and clarifications are released on weekdays, with a notable prevalence of clarification announcements during these times. This pattern underscores the strategic timing of rumor dissemination and clarification releases, aligning with market operations and investor attention. Figure A4 reveals the varied response times of companies to rumors, with the most companies addressing them by the following trading day showing highly efficient investor relations and a

[8] We understand the importance of rumors being clarified within a single day, as this more accurately demonstrates the effect of promptly published clarifications in mitigating the stock price volatility induced by rumors. However, our data limitations prevent us from accessing intraday trading, and therefore, we cannot assess the impact of rumors and their clarifications on stock prices within the trading day. Consequently, we have to exclude such rumor clarifications from our analysis.

[9] Appendix B5 provides a detailed explanation of this particular case.

[10] China's stock local trading hours are 9:30 am – 11:30 am and 1:00 pm – 3:00 pm Monday to Friday. In the data collection process, rumors from media sources may have a news release date but no release time. Therefore, such rumors are recorded as 0:00am, which indicate they are effective on the current/next trading day.

desire to avoid regulatory punishment. However, the delay in clarification could worsen the impact of the rumor on the company's stock performance and investor sentiment.

Each rumor-clarification pair has the information including the date and time of the rumor's initial appearance on the Baidu (or Google) search engine, [11] the effective date of the rumor and clarification announcement, and the number of interval days between the clarification and the corresponding rumor (clarification effective date – rumor effective date).

We manually examine rumors and clarification announcements to determine the type of rumor-clarification pair. To determine the veracity of each rumor, we classify the clarification announcement as true or false. We evaluate the rumor's tonality as positive, negative, or neutral, the event type such as Mergers and Acquisitions (M&A), asset reorganization, public offering, corporate performance, violation of laws or rules ("red alert"), and others, and its source, either traditional news media or social media. This hand-collected dataset is the most comprehensive collection of rumor-clarifications in the Chinese stock market literature.

Appendix B details the definitions of our manually collected rumors and clarification data. We also obtain the stock-level and firm-level data from CSMAR database. We extract daily trading data for each stock, including the closing price, trading volume, market capitalization and market return data (the value-weighted average return of all the A-shares traded on the SSE and SZSE respectively).[12] Moreover, we collect short selling data for stocks in China. Firm-level data including the firm size and firm leverage for the rumor-clarification pair related stock.

[11] We use Baidu, which is the dominating research engine, as our primary source, and switch to Google when Baidu falls short. This is because Baidu, complying with Chinese regulations, sometimes may filter out false news once clarified. Google, not subject to these constraints, maintains a more complete archive of rumor information, enabling us to collect a broader range of data on false rumors.

[12] In China stock market, price limit caps daily stock price fluctuation between +10% and -10%. To ensure accuracy in calculating abnormal volatility, we've clipped all returns to the [-10%, +10%] range. Any return beyond 10% is clipped to 10%, and anything below -10% is clipped to -10%, keeping out-of-range values within these boundaries.

3.2 Descriptive Statistics

Table 2 presents descriptive statistics, showing an average SIZE of 22.154 and BTM of 5.687. About 45% of the listed companies are SOEs. The average leverage is 0.494, TobinQ is 2.066, and ROA is 0.024. Social media accounts for about half of rumor dissemination. The average cumulative abnormal volatility is 0.022 at rumor onset, rising to 0.033 with public circulation. It remains elevated at 0.025 shortly after clarification and gradually decreases to 0.02 within 20 days, indicating a longer-term decline.

In Appendix C, the Confusion Matrix C1 illustrates that over 80% of sampled news items are false, with negative news prevailing over positive. An unconditional expectation—assuming no prior knowledge—suggests an 86% likelihood of news being false, highlighting the difficulty market participants face in identifying truthful information.

Table C2 presents that false rumors dominate across all market caps, comprising 87% of false rumors, with 50.3% being negative. True rumors make up just 13%. Large-cap companies are most implicated, involved in 41.8% of rumors. This reflects a market bias towards pessimistic speculation, highlighting the needs for investors to critically assess information. False rumors predominantly focus on larger firms, possibly due to their greater media visibility.

In Table C3, Corporate Operation & Performance events account for 41.9% of rumors, indicating that the complexities of corporate activities are hotbeds for speculation. Asset Reorganization and Red Alert events also see significant rumor activity, at 10.4% and 27.3% respectively, driven by the high stakes of these situations. M&A, and Public Offerings, though less frequent, are still notable at 6.6% and 5.2%, illustrating the sensitivity of the market to transformative corporate events.

Table C4 identifies traditional media (52.1%) and social media (47.9%) as primary rumor channels, with traditional media favoring negative rumors (27.9%) and social media distributing a more balanced mix.

Table C5 outlines the temporal trends of rumor prevalence from 2007 to 2022, peaking in 2013 and declining significantly post-2020, likely due to enhanced regulatory measures and the maturing investor base. This trend suggests a gradual shift towards a more stable and discerning market environment, less susceptible to disruptive rumors.

4. Methodology

4.1 Event Study Methodology

Our study modifies the standard event study approach by taking two consecutive event dates to quantify abnormal volatility surrounding the event days. We utilize the two consecutive event dates to illustrate the rumor-clarification process because the objective is to examine the stock price reactions to rumors and the extent to which clarifications mitigate abnormal volatility induced by rumors. Our approach and the process of rumor-clarification by using the two consecutive event windows, consisting of the rumor event window and the clarification event window, details see Figure 1.

We define the estimation window as the period from 130 days prior to 10 days prior to the rumor date. The rumor event window starts the period from 10 days prior to the rumor date (inclusive) up to the day of clarification (exclusive), capturing the period during which the market is exposed to the rumor and its effects. We further split the rumor event window into private rumor period, during which rumors have not been released by press, and public rumor period, during which rumors are published by press. The clarification window starts from when effective day of clarification announcement. It is noteworthy that the interval between rumors and clarifications varies, with some companies clarifying within a day, while others take several days. Figure 2 illustrates the number of days it takes for companies to issue clarification announcements subsequent to the initial rumor release. The following clarification event window begins on the day of clarification (inclusive) and extends for a period of 60 days thereafter (inclusive), representing the time frame during which the market digests and responds to the clarifying information.

We use the CAPM market model to estimate the beta and constant for individual stock during the 120-days estimation window with a minimum pre-event length of 120 trading days.

$$R_{i,t} = \alpha_i + \beta_i RM_{j,t} + \varepsilon_{it}$$

Where R_{it} denotes stock i's return on day t, and RM_{jt} represents stock i's home exchange j's index return, i.e., Shanghai or Shenzhen Stock Exchange.

The abnormal returns and cumulative abnormal returns of stock i are calculated as,

$$AR_{i,t} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i RM_{j,t}$$

4.2 Abnormal Volatility

We follow Griffin et. al. (2011) to define abnormal volatility is the absolute value of abnormal return from CAPM model. While the day intervals between the rumor and clarification dates is dependent on how promptly companies release clarification announcements. To account for variation in interval days and measure cumulative abnormal volatility between rumors and clarifications, we calculate average abnormal volatility during both periods and treat the interval between the rumor and clarification period (exclusive) as one day. This assumption assumes a one-day interval between the two events (rumor to clarification). We also construct normal volatility, which is the average abnormal volatility during estimation window. The cumulative abnormal volatility is the average abnormal volatility from day t_1 to t_2.

Abnormal Volatility:

$$AVOL_{i,t} = |AR_{i,t}| \tag{1}$$

Normal Volatility:

$$Vol_{normal} = \frac{1}{N}\sum_{i=1}^{N}(\frac{1}{120}\sum_{t=-130}^{-10}|AR_{i,t}|) \tag{2}$$

Cumulative Abnormal Volatility:

$$CAVOL_{t_1,t_2} = \frac{1}{N}\sum_{i=1}^{N}(\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}|AR_{i,t}|) \tag{3}$$

We follow Griffin et.al. (2011) to use non-parametric rank t-test from Corrado (1989) to test if the event volatility if higher than the normal volatility. In particular, we use simplified version modified by Ataullah et.al. (2011).

$$tstat_t = \sqrt{\frac{3}{N(T^2 - 1)}}\sum_{i=1}^{N}[2K(|AR_{i,t}|) - (T + 1)] \tag{4}$$

Where N is the number of event in the sample, K(·) is rank operator,and K($Vol_{i,t}$) is the rank of abnormal volatility of event *i* at time *t*, T is the total number of days in the estimation and event period (191 days).[13] This test stats is a non-parametric test that ranks all abnormal volatility in the event window and then tests if the average rank of the each event date abnormal

[13] In our case, the 191 days are consisting of 120 days estimation window, 10 days private rumor window, 1 day public rumor window and 60 days clarification window.

volatility is significantly different from the expected average rank under the null hypothesis of no abnormal volatility.

We further investigate the abnormal volatility over an event window follow Ataullah et.al. (2011). i.e., whether averaged cumulative event abnormal volatility is different from normal abnormal volatility.

$$tstat_M = \sqrt{\frac{3}{NM(T+1)(T-M)}} \sum_{i=1}^{N} [2K\left(\sum_{t=t_1}^{t_1+M} |AR_{i,t}|\right) - M(T+1)] \quad (5)$$

Where M is the length of the event window.

4.3 Predict the Veracity of Rumors

To test Hypothesis 3, whether the veracity of rumors can be predicted, we employ a logistic regression to examine what are the factors associated with the accuracy of the rumors (Jia et al., 2017).

$$\begin{aligned} \mathrm{TrueRumors}_{i,t} &= \alpha + \beta_1 \mathrm{SocialMedia_{i,t}} + \beta_2 \mathrm{SOE_{i,t}} + \beta_3 \mathrm{Neg}_{i,t} \\ &+ \beta_4 \ln\left(1 + \mathrm{CAVOL_{[R-10,R-1],i,t}}\right) + \beta_5 \ln\left(1 + \mathrm{AVOL_{[R],i,t}}\right) \\ &+ \sum_{k=6}^{12} \beta_k Controls_{k,i,t} + \varepsilon_{i,t} \end{aligned} \quad (6)$$

In equation (6), the dependent variable is a dummy variable indicating the veracity of the rumors, which equals to one if rumors are confirmed true in the clarification announcement and 0 otherwise.

The credibility of rumors is enhanced by the media regardless of veracity. Not all media reports are factual and they are intertwining truth and lies. Allcott & Gentzkow (2017) find that trust in information accessed through social media is lower than trust in traditional outlets. Investors' increased distrust of news from the social media platforms, but not other forms of news media. To test news sources, we include a dummy variable (SocialMedia) to indicate if the source is from social media, as it plays a negative role in impeding price discovery (Jia et.al. 2020). Appendix C shows that both traditional and social media are equally likely to be wrong about rumors. SOEs play an important role in Chinese companies (Lin et al., 2020). We include a dummy variable, Neg, which equals 1 if the rumor is about a negative news. Additionally, we analyse the cumulative abnormal volatility during both the private and public rumor periods to determine if price movements can predict the veracity of rumors. In all the regression equations in this paper, we include a set of control variables: firm size (Size), market-to-book ratio (BTM), leverage (Lev), a dummy variable indicating whether the stock can be shorted (Short), return on assets (ROA), the Tobin's Q ratio (TobinQ), and price momentum (Mom). At last, we also control for industry and year fixed effect to remove the industry and year heterogeneous effect.

4.4 Determinants of Abnormal Volatility

Following Griffin et al. (2011), we use the following estimation equation to investigate the determinants of rumor effects [Equation (7)] and clarification effects [Equation (8)].

$$\begin{aligned}\ln\left(1+\mathrm{CAVOL}_{[R-10,R],i,t}\right), \ln\left(1+\mathrm{AVOL}_{[R],i,t}\right) &= \alpha+\beta_1\mathrm{SocialMedia}_{i,t}+\beta_2\mathrm{SOE}_{i,t}+\beta_3\mathrm{Neg}_{i,t} \\ &+\left(\beta_4\mathrm{CAVOL}_{[\mathrm{R-10,R-1}]i,t}\right)+\sum_{k=5}^{11}\beta_k Controls_{k,i,t}+\varepsilon_{i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\ln\left(1+\mathrm{CAVOL}_{[C,C+1],i,t}\right), \ln\left(1+\mathrm{CAVOL}_{[C,C+19],i,t}\right) &= \alpha+\beta_1\mathrm{SocialMedia}_{i,t}+\beta_2\mathrm{SOE}_{i,t}+\beta_3\mathrm{Neg}_{i,t}+\beta_4\mathrm{True}_{i,t} \\ &+\beta_5\mathrm{CAVOL}_{[\mathrm{R-10,R-1}]i,t}+\beta_6\mathrm{AVOL}_{[\mathrm{R}],i,t}+\beta_7\mathrm{Interval}_{i,t} \\ &+\sum_{k=8}^{14}\beta_k Controls_{k,i,t}+\varepsilon_{i,t}\end{aligned} \tag{8}$$

Where $\mathrm{CAVOL}_{[\mathrm{R-10,R}]}$ and $\mathrm{AVOL}_{[\mathrm{R}]}$ are the cumulative abnormal volatility during rumor period and abnormal volatility on the rumor release day, $\mathrm{CAVOL}_{\mathrm{C,C+1}}$ and $\mathrm{CAVOL}_{\mathrm{C,C+19}}$ are the cumulative abnormal volatility during short-term and long-term clarification periods.

The effectiveness of a clarification announcement depends on various factors. To test the clarification effect, we include rumors effect ($\mathrm{CAVOL}_{[R-10,R]}$) and an indicator whether the rumors are true or false (True). The credibility of the source (SocialMedia), the timing of the announcement (Interval). The timing of the clarification announcement can also be crucial for its effectiveness. If the clarification comes too late or is not widely distributed, the rumor may already have spread too far to be effectively countered. Hence, we include number of interval days between the effective date of rumor release and the effective date of clarification announcement. We control for momentum (Mom), the tendency for stocks that have performed well in the past to continue performing well in the near future, and vice versa for poorly performing stocks, to avoid confounding the relationship between rumors, clarifications, and stock price movements (Jegadeesh & Titman, 1993).

5 Empirical Results

5.1 Abnormal Volatility Around Rumors and Clarifications

Information can alter investors' beliefs in the future cash flow or the discount factor, and thus the value of the stock. The tonality of rumors posts either risk of opportunity with regard to stock, and the veracity of the rumor could result in investors adjusting position to mitigate additional risk or return seeking. We categorize rumors and clarifications into four distinct types by their tonality and veracity: True Positive rumors, True Negative rumors, False Positive rumors, and False Negative rumors.

Table 3 shows the abnormal volatility with the non-parametric test statistic starting from five trading days before the release of rumors [R-5] till ten trading days after the clarification [C+9]. Column (1) to Column (4) are the subgroups of the full sample based on the tonality and veracity of rumor-clarification. Column (1), (2) and (4) show that the abnormal volatility is significant a few days before the rumors release, and vanished a few days after the clarification, whereas the abnormal volatility is significant over the whole examining period in Column (3). This indicates that stocks become unsettled even during the private rumor period and settled down in about three days after the clarification. However, the uncertainty for False Positive rumors exists over the examined period, and the abnormal volatility disappears over the longer term (around 28 trading days) as shown in Figure 3.

Figure 3 depicts the longer period of abnormal volatility. This figure clearly demonstrates that abnormal volatility elevates from the private rumor period and peaks at public rumor period, and the abnormal volatility starts to decline from the clarification announcement day. This finding indicates that rumors are associated with abnormal volatility, and clarification announcements mitigate abnormal volatility induced by rumors.

In addition, the magnitudes of abnormal volatility of Positive rumors are higher than Negative rumors on rumor day.

5.2 Predict the Veracity of Rumors

Table 4 shows the results of the factors that can be utilized to predict the veracity of rumors. Column (1) – (3) shows the results of Full sample, Negative rumors and Positive rumors, respectively.

In column (1) and (3), the coefficients of $AVOL_{[R]}$ are negative and significant, indicating that the level of abnormal volatility at the rumor release day is negatively related to the tonality of rumor. As the majority of trading volume in China is from uninformed individual investors, the results show that the larger uncertainty introduced by the rumor release for positive rumors are less likely to be true. This has potential implication for investors that for positive rumors, the elevated abnormal volatility is not a negative indicator of the credibility of the rumor.

Additionally, the coefficients for SocialMedia and SOE are negative and significant for positive rumors, indicating that positive rumors originating from social media and concerning SOEs are less likely to be true. This could be because investors show a keen interest in SOE firms, making them prime targets for speculators. Furthermore, speculators and opportunists can easily disseminate rumors through social media.

5.3 Determinants of Abnormal Volatility

Both rumors and clarifications impact abnormal volatility. We further investigate the factors driving these effects. Exploring the determinants of abnormal volatility during rumor and clarification periods provides crucial insights into market dynamics.

Table 5 presents the results. Panel A shows the estimation results using Equation (7). The dependent variables in column (1)-(3) are the cumulative abnormal volatility during rumor period [R-10, R], and those in column (4)-(6) are the abnormal volatility on rumor day [R]. The coefficients of Negative (dummy variable) in column (1) and (4) are negative and significant, indicating that the positive rumors are associated with higher volatility. This finding is consistent with the result show in Figure 3 that positive rumors is associated with higher abnormal volatility after controlling confounding factors.

The coefficients on $CAVOL_{[R-10,\ R-1]}$ are positive and significant, suggesting the abnormal volatility on the rumor day are elevated by the cumulative abnormal volatility in the private rumor period. Such continuation of abnormal volatility would assist the market speculators in boosting the unsettlement and uncertainty of the rumors when released.

Another interesting result is that the coefficients on SOE in column (5) and (6) are significant but with opposite signs, i.e., SOE firms are associated with higher abnormal volatility if rumor is positive and lower volatility if rumor is negative. This suggests the preference of investors regarding SOEs.

Panel B shows the estimation results using Equation (8), where dependent variables in column (1)-(3) are cumulative abnormal volatility during short-term clarification period, and those in column (4)-(6) are during long-term clarification period.

The results are similar to the results in Panel A. The coefficients on Neg (dummy variable) are negative and significant, and the coefficients on CAVOL and AVOL during rumor period are positive and significant. These findings further confirm that positive rumors generate higher abnormal volatility and the continuation of abnormal volatility, i.e., abnormal volatility tends to beget further abnormal volatility, akin to a momentum effect in the market.

6 Additional Tests

6.1 Quadratic Abnormal Volatility

Brown and Warner (1980,1985) identified the testing problems created by event-induced increase in variance. They note that if the variance is underestimated, the test statistic would incorrectly reject the null hypothesis more frequently than appropriate, even when the average abnormal performance is zero.

To further test the robustness of the results, we follow Devos et.al. (2015) and construct the abnormal volatility by dividing the square of abnormal return during event period and the variance of the abnormal volatility (residual term) during estimation period. This quadratic cumulative abnormal volatility is the average quadratic abnormal volatility during the examined period.

Quadratic Abnormal Volatility:

$$QAVOL_{i,t} = \frac{AR_{i,t}^2}{\sigma_i^2} \tag{3}$$

Quadratic Cumulative Abnormal Volatility:

$$QCAVOL_{n_1,n_2} = \frac{1}{N}\sum_{i=1}^{N}(\frac{1}{n_2 - n_1 + 1}\sum_{t=n_1}^{n_2}\frac{AR_{i,t}^2}{\sigma_i^2}|) \qquad (4)$$

If abnormal volatility is between (greater than) 0 and 1, the stock is considered to have smaller than normal (greater than normal) volatility. Follow Devos et al. (2015) we calculate one-tailed t-statistics to test the null hypothesis that event window abnormal volatility is smaller or equal to 1.

The results are show in Table 6 and Figure 4. Comparing the results from the main measure as shown in Table 3 and Figure 3, the patterns are consistent, though the magnitudes are different due to the measurements. The test statistics of the main approach seems to be more consistent with what would be expected from the analysis. One possible explanation is that the main approach is more conservative and highlights only a few instances of significance. The quadratic approach is more relaxed, providing lesser discrimination between different abnormal volatility values. To provide further confidence with the findings, we conduct bootstrap test.

6.2 Bootstrap Algorithm

Parametric tests assume explicitly that the underlying assumptions of the theoretical tests are satisfied. Which means, the error terms are normally distributed and are not serially correlated. If any of these assumptions is violated, the test statistic is biased, and the results could be misleading. Efron (1979) uses bootstrap methodology in which normality is not a crucial assumption and serial correlation is dealt with. Based on this technique, the empirical distribution of the CAVOLs is simulated under the null hypothesis and is compared with the CAVOL in the period following the rumor clarification events.

We further conduct a bootstrap method to evaluate the level of abnormal volatilities. The procedures of generating the distribution of abnormal volatility to compute the bootstrap p-value are below:

1. For each of the rumor-clarification pairs, we randomly select dates for the rumor and clarification, ensuring the time interval between rumor and clarification aligns with the actual interval.
2. We estimate the abnormal volatility using both approaches and save the abnormal volatility.
3. We re-run Step 1&2 one thousand times for each rumor-clarification pair. We have a matrix of the event window size * number of simulations (71*1,000) for each rumor-clarification pair. We have 2,127 matrices in total.
4. We calculate the cross-sectional average of abnormal volatility measure for each order of simulation in each rumor-clarification pair, i.e., average across 2,127 events for simulation 1 till simulation 1,000, ending up with 1,000 sets of abnormal volatility measure across event period (71*1,000). To calculate the p-value for abnormal volatility in the event period, we use the top 90%,95% and 99% value as the threshold for 90%,95% and 99% confidence interval.
5. To calculate the confidence intervals for subsamples, e.g., Positive True, Negative False, we re-run Step 4 by selecting corresponding subsample bootstrap abnormal volatility estimates.

In addition, to ensure that there is enough estimation window period, the random selection window is clipped by minimum estimation period (120 days) and clarification event window period (60 days). For example, if the stock available (for Event X) trading period is from 1/1/2010 to 31/12/2020, the random selected rumor date is truncated by 120 trading days (minimum estimation period) at the front end, i.e., roughly 1/5/2010, and 60 trading days (clarification period) + intervals between rumors and clarification (e.g., 3 days) at the long end, i.e., around 28/10/2020. The 1,000 bootstraps for Event X are randomly selected from 1/5/2020 to 28/10/2020, so that we can ensure that there is enough estimation window and event window.

The results of bootstrap approach are presented in Table 7 and illustrated in Figure 5. The values of the histogram chart represent the 90% threshold of bootstraps for different types of rumors. What we are comparing is that if the value of any actual data (line chart) is greater than the bootstrap threshold value, the result is significant.

The results are largely consistent with the main approach and confirm that abnormal volatility is mainly concentrated around rumor and clarification, which is abnormal volatility accelerated over the rumor period and clarification curbed the abnormal volatility.

7 Conclusion

We study the interplay among rumors, clarifications, and stock market volatility in the Chinese stock market. Our findings reveal that unverified rumors, regardless of their tone or accuracy, significantly elevate abnormal volatility, with the most pronounced effects occurring on the day of rumor release. Verified clarifications serve to reduce market uncertainty and facilitate a return to stability, though their effectiveness is limited, particularly in the case of false positive rumors, which require extended periods to stabilize market conditions. These results point to persistent inefficiencies in the market's ability to process and react to unverified information in China.

This research provides several key contributions. First, it challenges prevailing assumptions by demonstrating that positive rumors have a more substantial impact on market volatility than negative rumors, suggesting that speculative traders may leverage positive rumors to manipulate market dynamics. Second, the analysis highlights that larger firms, SOEs, and entities operating in highly regulated environments possess greater capacities to address misinformation, though positive rumors originating from social media or targeting SOEs are less likely to align with reality. Third, the persistence of abnormal volatility throughout the rumor clarification process demonstrates that unverified information creates ongoing uncertainty, even after clarifications are issued.

Methodologically, this study advances the literature by introducing a dual-event study framework focused on abnormal volatility, enabling more precise analysis of market reactions to rumors and their clarifications. This approach bridges theoretical models of market behavior with empirical observations. By examining China’s unique regulatory framework for clarification announcements, the study provides important insights into how institutional interventions can help mitigate volatility in emerging markets. The findings emphasize the importance of policies that improve the dissemination and accuracy of information to support market stability.

Tables

Table 1: Rumor-Clarification Pair Selection Criteria

This table shows sample selection process applied from an initial 3,515 clarifications to 2,127 valid rumor-clarification pairs used in this analysis, covering the period from January 2007 to December 2022. Detailed variable definitions are in Appendix 1.

Selection Criteria	Observations
Clarification announcements between 2007 and 2022	3515
Rumors not available [14]	3127
Remove two clarifications from the same stock within 120 days	3119
Interval <1	2885
Rumors and clarifications during stock halts [15]	2251
Remove neutral rumors	2229
Rumor-clarification pairs used for summary statistics	**2229**
Before-rumor less than 120 +10 trading days	2139
Post-clarification less than 60 trading days	2127
Final rumor clarification pairs for estimation and regression	**2127**
Number of unique stocks	**1376**

[14] The corresponding rumors are not available, which could be due to dated rumors been removed from websites. A single clarification announcement addresses multiple issues, unrelated to rumors as per CSRC regulations. Clarification announcement not caused by rumors. This means that under CSRC rule, if the share price suddenly rises or falls by 10% without any prior clarification by the company, the company must immediately investigate and clarify the key drivers of the significant price changes. Patel & Michayluk (2016) shows several causes of significant price movements, including liquidity trading, investor sentiment, liquidity shocks, private information leakage, and public information. Therefore, if the clarification clarifies the key drivers of the price change is associated with other reason rather than public or private rumors, we delete such clarification announcements in our sample.

[15] The particular case is explained in Appendix B5.

Table 2： Descriptive Statistics

This table reports descriptive statistics, including mean values, standard deviations (SD), and the 25th (P25), 50th (P50), and 75th (P75) percentiles for key variables. Definitions for each variable can be found in Appendix 1.

Var.	**Count**	**Mean**	**SD**	**P25**	**P50**	**P75**
Size	2127	22.154	1.359	21.132	22.003	23.094
BTM	2127	5.687	0.757	5.230	5.767	6.262
Mom	2127	0.091	0.347	-0.164	0.017	0.305
SOE	2127	0.452	0.498	0.000	0.000	1.000
Short	2127	0.219	0.414	0.000	0.000	0.000
Lev	2127	0.494	0.210	0.336	0.511	0.667
TobinQ	2127	2.066	1.063	1.248	1.693	2.599
ROA	2127	0.024	0.074	0.008	0.029	0.064
Interval	2127	4.050	7.268	1.000	2.000	4.000
SocialMedia	2127	0.472	0.499	0.000	0.000	1.000
$CAVOL_{R-10,R}$	2127	0.022	0.012	0.013	0.020	0.028
$AVOL_{R}$	2127	0.033	0.028	0.011	0.023	0.047
$CAVOL_{C, C+1}$	2127	0.025	0.020	0.010	0.020	0.035
$CAVOL_{C, C+19}$	2127	0.020	0.010	0.013	0.018	0.025

Table 3: Abnormal Volatility Around Rumors and Clarification

This table presents the average abnormal volatility around rumor events and subsequent clarifications, categorized by rumor type. It includes non-parametric test statistics for 5 days before rumors release and 10 days after clarification announcements. Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. T-statistics are shown in parentheses, and variable definitions are provided in Appendix 1.

Abnormal Volatility (AVOL) with Non-parametric Test Statistics

	(1)	(2)	(3)	(4)
	True Positive	**True Negative**	**False Positive**	**False Negative**
R-5	0.021	0.018	0.021*	0.02
	0.429	1.08	1.582	1.274
R-4	0.019	0.018	0.022***	0.021***
	-0.809	-0.244	3.392	2.791
R-3	0.021	0.021	0.022***	0.02***
	0.305	1.053	2.41	2.325
R-2	0.023	0.024***	0.023***	0.021***
	0.365	3.074	3.452	2.957
R-1	0.03***	0.022*	0.027***	0.022***
	4.113	1.63	6.666	3.896
R	0.039***	0.024***	0.045***	0.026***
	7.196	5.537	24.261	13.97
C	0.036***	0.02	0.036***	0.021***
	5.824	1.054	18.422	5.224
C+1	0.028**	0.02**	0.028***	0.021***
	2.142	1.764	11.021	3.917
C+2	0.026***	0.018	0.025***	0.019**
	3.262	1.212	6.553	1.886
C+3	0.024	0.019	0.024***	0.019
	1.276	0.352	5.984	0.243
C+4	0.025*	0.017	0.023***	0.018
	1.541	-1.121	4.207	-0.317
C+5	0.021	0.018	0.022***	0.018
	0.828	0.366	3.283	-0.017
C+6	0.02	0.015	0.023***	0.018
	-0.014	-1.49	4.827	0.241
C+7	0.02	0.018	0.023***	0.018
	-0.071	1.176	6.136	0.009
C+8	0.02	0.017	0.022***	0.019
	0.487	-0.795	2.581	1.019
C+9	0.024**	0.017	0.021***	0.019
	1.806	-0.348	3.443	1.277

Table 4: Predict the Veracity of Rumors

This table presents logistic regression results for the following equation:

$$\mathrm{Realized}_{i,t} = \alpha + \beta_1 \mathrm{SocialMedia}_{i,t} + \beta_2 \mathrm{SOE}_{i,t} + \beta_3 \mathrm{Neg}_{i,t} + \beta_4 \ln\left(1 + \mathrm{CAVOL}_{[R-10,R-1],i,t}\right) + \beta_5 \ln\left(1 + \mathrm{AVOL}_{[R],i,t}\right) + \sum_{k=6}^{12} \beta_k Controls_{k,i,t} + \varepsilon_{i,t}$$

It predicts whether the rumor is realized. The dependent variable is binary, equal to 1 if the rumor is realized as true news on the clarification date and 0 if false. The analysis is performed on the full sample, as well as separately for negative and positive rumors. The table displays the coefficients with t-statistics in parentheses. Significance levels are denoted by ***, **, and * for 1%, 5%, and 10%, respectively. Standard errors are clustered by rumor-clarification pair (event). Year and industry fixed effects are included. Variable definitions are provided in Appendix 1.

Whether Rumor is Realized on Clarification Date			
	(1)	**(2)**	**(3)**
Dependent Variable: Probability of Rumor Realization	Full Sample	Negative Rumors	Positive Rumors
	(t_stats)	(t_stats)	(t_stats)
SocialMedia	-0.082	0.121	**-0.465****
	(-0.621)	(0.713)	**(-2.186)**
SOE	-0.228	0.101	**-0.714*****
	(-1.609)	(0.557)	**(-3.218)**
Short	0.215	0.231	0.195
	(1.189)	(1.007)	(0.657)
Size	-0.086	-0.043	-0.167
	(-1.159)	(-0.438)	(-1.417)
BTM	0.408***	0.345**	0.49**
	(2.986)	(2.007)	(2.077)
Mom	-0.329	-0.014	-0.666**
	(-1.59)	(-0.049)	(-2.076)
Lev	1.09***	0.835*	1.563**
	(2.862)	(1.702)	(2.545)
ROA	0.781	-1.356	5.897***
	(0.826)	(-1.226)	(2.824)
TobinQ	0.247***	0.268**	0.173
	(2.728)	(2.336)	(1.119)
Neg	-0.04		
	(-0.277)		
$\ln(1+\mathrm{CAVOL}_{[R-10,\,R-1]})$	4.612	-3.472	13.551
	(0.761)	(-0.418)	(1.457)
$\ln(1+\mathrm{AVOL}_{[R]})$	**-5.535****	-3.003	**-6.038***
	(-2.095)	(-0.74)	**(-1.688)**
const	-3.163*	-3.796*	-1.758
	(-1.915)	(-1.759)	(-0.658)
Industry & Year FE	Yes	Yes	Yes
Obs.	2127	1226	901
Pseudo R^2	0.016	0.017	0.055

Table 5: Determinants of Abnormal Volatility

This table presents OLS regression results for the following equation:

$$\text{Private/Public Period CAVOL}_{i,t} = \alpha + \beta_1 \text{SocialMedia}_{i,t} + \beta_2 \text{SOE}_{i,t} + \beta_3 \text{Neg}_{i,t} + \beta_4 \text{Previous CAVOL}_{i,t} + \sum_{k=5}^{11} \beta_k Controls_{k,i,t} + \varepsilon_{i,t}$$

It assesses the determinants of abnormal volatility during the private and public rumor periods for the full sample, also separately for positive and negative rumors. The table displays regression coefficients with t-statistics in parentheses, and significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by rumor-clarification pair (event). Year and industry fixed effects are included, with variable definitions provided in Appendix 1.

Panel A: Private and Public Rumor Period						
Dependent Variable	**(1)** ln(1+ CAVOL [R-10, R])	**(2)** ln(1+ CAVOL [R-10, R])	**(3)** ln(1+ CAVOL [R-10, R])	**(4)** ln(1+ AVOL [R])	**(5)** ln(1+ AVOL [R])	**(6)** ln(1+ AVOL [R])
	Full Sample	Positive Rumors	Negative Rumors	Full Sample	Positive Rumors	Negative Rumors
	(t_stats)	(t_stats)	(t_stats)	(t_stats)	(t_stats)	(t_stats)
SocialMedia	-0.0	-0.0	0.0	0.002	0.004**	0.0
	(-0.016)	(-0.119)	(0.205)	(1.408)	(2.015)	(0.281)
SOE	-0.001	0.0	-0.001*	0.0	**0.005****	**-0.002***
	(-1.287)	(0.291)	(-1.737)	(0.361)	**(2.245)**	**(-1.781)**
Short	-0.001	-0.003***	0.0	-0.001	-0.006*	0.001
	(-1.557)	(-2.789)	(0.279)	(-0.426)	(-1.705)	(0.279)
Size	-0.001***	-0.001	-0.001***	-0.0	-0.003**	0.001
	(-3.597)	(-1.438)	(-3.671)	(-0.695)	(-2.507)	(1.638)
BTM	-0.002***	-0.002**	-0.002***	-0.001	0.002	-0.003**
	(-4.678)	(-2.475)	(-3.546)	(-0.819)	(0.864)	(-2.067)
Mom	0.008***	0.005***	0.01***	-0.002	-0.006*	0.001
	(9.784)	(4.357)	(9.044)	(-0.868)	(-1.726)	(0.522)
Lev	0.0	-0.001	0.002	0.002	0.003	0.001
	(0.254)	(-0.303)	(0.895)	(0.453)	(0.501)	(0.337)
ROA	-0.009***	-0.01**	-0.009**	-0.012	-0.041***	0.003
	(-2.754)	(-1.987)	(-2.157)	(-1.409)	(-2.697)	(0.327)
TobinQ	0.0	-0.0	0.0	-0.001	-0.002	0.0
	(0.544)	(-0.144)	(0.988)	(-0.67)	(-1.47)	(0.205)
Neg	**-0.002*****			**-0.017*****		
	(-3.984)			**(-14.159)**		
ln(1+CAVOL[R-10, R-1])				**0.45*****	**0.319*****	**0.525*****
				(8.279)	**(3.227)**	**(8.859)**
const	0.057***	0.048***	0.061***	0.05***	0.093***	0.003
	(9.59)	(5.178)	(7.85)	(3.256)	(3.342)	(0.184)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2127	901	1226	2127	901	1226
R^2	0.138	0.088	0.172	0.132	0.053	0.095

This table presents OLS regression results for the following equation:

$$\text{Short/ Long} - \text{term Clarification Period CAVOL}_{\text{i,t}} = \alpha + \beta_1\text{SocialMedia}_{i,t} + \beta_2\text{SOE}_{i,t} + \beta_3\text{Neg}_{i,t} + \beta_4\text{True}_{i,t} + \beta_5\text{Private Rumor CAVOL}_{i,t} + \beta_6\text{Public Rumor AVOL}_{i,t} + \beta_7\text{Interval}_{i,t} + \sum_{k=8}^{14}\beta_k Controls_{k,i,t} + \varepsilon_{i,t}$$

This table presents OLS regression results for the determinants of abnormal volatility (CAVOL) during short and long clarification periods, segmented by positive and negative rumors. It reports coefficients and t-statistics, with significance levels denoted by ***, **, and * for 1%, 5%, and 10%, respectively. Standard errors are clustered by rumor-clarification pair (event). Year and industry fixed effects are included, with variable definitions provided in Appendix 1.

Panel B: Clarification Period						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable	ln(1+ CAVOL $_{[C, C+1]}$)	ln(1+ CAVOL $_{[C, C+1]}$)	ln(1+ CAVOL $_{[C, C+1]}$)	ln(1+ CAVOL $_{[C, C+19]}$)	ln(1+ CAVOL $_{[C, C+19]}$)	ln(1+ CAVOL $_{[C, C+19]}$)
	Full Sample	Positive Rumors	Negative Rumors	Full Sample	Positive Rumors	Negative Rumors
	(t_stats)	(t_stats)	(t_stats)	(t_stats)	(t_stats)	(t_stats)
SocialMedia	0.001*	0.002	0.001	0.0	-0.0	0.001
	(1.781)	(1.194)	(0.932)	(1.037)	(-0.353)	(1.645)
SOE	0.0	0.001	-0.0	0.0	0.001*	-0.001
	(0.382)	(0.706)	(-0.205)	(0.09)	(1.875)	(-1.587)
Short	-0.001	-0.002	0.0	-0.001	-0.001*	-0.0
	(-0.538)	(-0.859)	(0.272)	(-1.568)	(-1.716)	(-0.431)
Size	-0.001**	-0.002**	-0.001	-0.001**	-0.001**	-0.0**
	(-2.541)	(-2.318)	(-1.295)	(-2.574)	(-2.042)	(-2.014)
BTM	-0.0	0.002	-0.002*	-0.001***	-0.001**	-0.001**
	(-0.244)	(1.408)	(-1.955)	(-2.93)	(-2.229)	(-2.117)
Mom	0.004***	0.007***	0.002	0.003***	0.004***	0.003***
	(2.979)	(3.159)	(0.98)	(5.463)	(4.416)	(3.645)
Lev	0.001	0.002	0.001	0.0	-0.001	0.001
	(0.608)	(0.538)	(0.42)	(0.21)	(-0.453)	(1.016)
ROA	-0.014**	-0.013	-0.016**	-0.004*	-0.003	-0.005*
	(-2.457)	(-1.357)	(-2.518)	(-1.663)	(-0.761)	(-1.713)
TobinQ	-0.0	0.0	-0.0	0.0	0.0	0.0
	(-0.371)	(0.024)	(-0.603)	(0.763)	(0.27)	(0.638)
Neg	**-0.006*** **			**-0.002*** **		
	(-7.493)			**(-5.344)**		
True		0.002	-0.0		0.001	0.0
		(0.807)	(-0.337)		(1.629)	(0.17)
ln(1+CAVOL $_{[R-10, R-1]}$)	**0.308*** **	**0.342*** **	**0.281*** **	**0.263*** **	**0.285*** **	**0.245*** **
	(8.586)	**(5.423)**	**(6.536)**	**(16.784)**	**(10.817)**	**(12.614)**
ln(1+AVOL $_{[R]}$)	**0.2*** **	**0.202*** **	**0.191*** **	**0.083*** **	**0.085*** **	**0.081*** **
	(13.97)	**(9.261)**	**(9.35)**	**(13.262)**	**(9.371)**	**(8.742)**
Intervals	-0.0	0.0	-0.0	-0.0	0.0	-0.0
	(-0.291)	(0.397)	(-1.202)	(-0.264)	(0.959)	(-1.492)
const	0.041***	0.04**	0.037***	0.029***	0.034***	0.027***
	(4.102)	(2.254)	(3.122)	(6.758)	(4.628)	(4.985)

Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2127	901	1226	2127	901	1226
R^2	0.227	0.172	0.178	0.336	0.311	0.323

Table 6: Quadratic Abnormal Volatility

This table shows quadratic abnormal volatility with parametric test statistics for different rumor types from 5 days before rumors release to 10 days after clarifications. Significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels

Quadratic Abnormal Volatility with Parametric Test Statistics				
DV: QAVOL	**(1)**	**(2)**	**(3)**	**(4)**
	True Positive (t_stats)	**True Negative** (t_stats)	**False Positive** (t_stats)	**False Negative** (t_stats)
R-5	1.399	1.169	1.560***	1.738***
	(1.158)	(0.887)	(3.776)	(4.116)
R-4	1.430	1.426*	1.758***	1.885***
	(1.073)	(1.330)	(4.407)	(4.702)
R-3	1.625*	1.796***	1.713***	1.590***
	(1.644)	(2.440)	(4.418)	(4.203)
R-2	2.304**	2.154***	2.005***	1.611***
	(2.244)	(3.154)	(5.410)	(3.994)
R-1	4.287***	1.842***	2.884***	2.218***
	(3.080)	(2.606)	(7.904)	(5.467)
R	6.403***	2.098***	7.838***	2.819***
	(4.243)	(3.567)	(12.042)	(9.034)
C	5.353***	1.477**	4.654***	1.756***
	(3.236)	(1.814)	(11.145)	(5.671)
C+1	3.491**	1.417**	2.654***	1.545***
	(2.314)	(1.792)	(6.246)	(4.523)
C+2	3.072**	2.263*	2.140***	1.362***
	(1.694)	(1.454)	(6.318)	(3.144)
C+3	2.888**	1.183	2.032***	1.333***
	(1.955)	(1.104)	(5.579)	(2.897)
C+4	2.672**	1.222	1.830***	1.433***
	(2.157)	(0.858)	(4.674)	(2.748)
C+5	2.582*	1.268	1.800***	1.219***
	(1.611)	(1.220)	(4.815)	(2.377)
C+6	2.129	1.165	1.909***	1.204**
	(1.288)	(0.478)	(5.302)	(1.689)
C+7	2.191*	1.231	1.772***	1.333***
	(1.385)	(1.170)	(5.245)	(2.646)
C+8	1.715	1.376*	1.735***	1.276***
	(1.253)	(1.308)	(4.892)	(2.733)
C+9	3.094**	1.335	1.542***	1.461***

	(1.895)	(1.129)	(3.606)	(3.361)

Table 7: Bootstrap Approach

Panel A: Abnormal Volatility with Bootstrap Test P-value

This table shows abnormal volatility around rumor events, categorized by truthfulness, with bootstrap test p-values assessing the significance. Columns represent rumor types, and rows correspond to the days before (R) rumor and after (C) clarification, with significance levels marked by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

DV: AAVOL	**(1)**	**(2)**	**(3)**	**(4)**
	True Positive (t_stats)	**True Negative** (t_stats)	**False Positive** (t_stats)	**False Negative** (t_stats)
R-5	0.021*	0.018	0.021***	0.02***
	(0.069)	(0.514)	(0.069)	(0.142)
R-4	0.019	0.018	0.022***	0.021***
	(0.306)	(0.510)	(0.029)	(0.067)
R-3	0.021*	0.021***	0.022***	0.02***
	(0.052)	(0.052)	(0.018)	(0.153)
R-2	0.023***	0.024***	0.023***	0.021***
	(0.008)	(0.004)	(0.008)	(0.061)
R-1	0.03***	0.022***	0.027***	0.022***
	(0.000)	(0.018)	(0.000)	(0.018)
R	0.039***	0.024***	0.045***	0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
C	0.036***	0.02**	0.036***	0.021***
	(0.000)	(0.160)	(0.000)	(0.048)
C+1	0.028***	0.02**	0.028***	0.021***
	(0.000)	(0.137)	(0.000)	(0.049)
C+2	0.026***	0.018	0.025***	0.019**
	(0.000)	(0.505)	(0.000)	(0.309)
C+3	0.024***	0.019	0.024***	0.019**
	(0.001)	(0.313)	(0.001)	(0.313)
C+4	0.025***	0.017	0.023***	0.018
	(0.001)	(0.709)	(0.005)	(0.515)
C+5	0.021*	0.018	0.022***	0.018
	(0.065)	(0.514)	(0.020)	(0.514)
C+6	0.02	0.015	0.023***	0.018
	(0.164)	(0.958)	(0.008)	(0.545)
C+7	0.02	0.018	0.023***	0.018
	(0.154)	(0.542)	(0.003)	(0.542)
C+8	0.02	0.017	0.022***	0.019**
	(0.156)	(0.760)	(0.018)	(0.327)
C+9	0.024***	0.017	0.021***	0.019**
	(0.000)	(0.717)	(0.064)	(0.324)

Panel B: Quadratic Abnormal Volatility with Bootstrap P-value

This table displays the quadratic abnormal volatility after rumor clarification, assessed by bootstrap p-values across different types of rumors. The table spans days leading up to 5 days before rumor and following 10 days after clarification event, with significance indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

DV: QAVOL	(1)	(2)	(3)	(4)
	True Positive (t_stats)	**True Negative** (t_stats)	**False Positive** (t_stats)	**False Negative** (t_stats)
R-5	1.399	1.169	1.56**	1.738***
	(0.242)	(0.509)	(0.007)	(0.001)
R-4	1.43	1.426	1.758***	1.885***
	(0.221)	(0.224)	(0.000)	(0.000)
R-3	1.625	1.796**	1.713***	1.59***
	(0.106)	(0.052)	(0.003)	(0.007)
R-2	2.304***	2.154***	2.005***	1.611***
	(0.010)	(0.010)	(0.000)	(0.002)
R-1	4.287***	1.842**	2.884***	2.218***
	(0.000)	(0.040)	(0.000)	(0.000)
R	6.403***	2.098***	7.838***	2.819***
	(0.000)	(0.007)	(0.000)	(0.000)
C	5.353***	1.477	4.654***	1.756***
	(0.000)	(0.210)	(0.000)	(0.002)
C+1	3.491***	1.417	2.654***	1.545**
	(0.000)	(0.249)	(0.000)	(0.019)
C+2	3.072***	2.263***	2.14***	1.362
	(0.001)	(0.005)	(0.000)	(0.224)
C+3	2.888***	1.183	2.032***	1.333
	(0.001)	(0.554)	(0.000)	(0.305)
C+4	2.672***	1.222	1.83***	1.433
	(0.007)	(0.512)	(0.003)	(0.099)
C+5	2.582***	1.268	1.8***	1.219
	(0.006)	(0.460)	(0.002)	(0.649)
C+6	2.129**	1.165	1.909***	1.204
	(0.035)	(0.611)	(0.001)	(0.709)
C+7	2.191**	1.231	1.772***	1.333
	(0.018)	(0.512)	(0.006)	(0.301)
C+8	1.715	1.376	1.735***	1.276
	(0.125)	(0.302)	(0.007)	(0.514)
C+9	3.094***	1.335	1.542*	1.461
	(0.002)	(0.399)	(0.067)	(0.108)

Figures

Figure 1: Dual Event Structure

This figure illustrates a modified dual event study structure, comprising the estimation window [R_-130, R_-10), the rumor event window [R_-10, C), and the clarification event window [C, C_+59]. The rumor event window is divided into a private rumor period, starting 10 days before the rumor release, capturing any information leakage or 'word-of-mouth' market movement, and a public rumor period from the rumor release (R) to the clarification (C). This structure outlines the sequence and duration of each phase in the analysis.

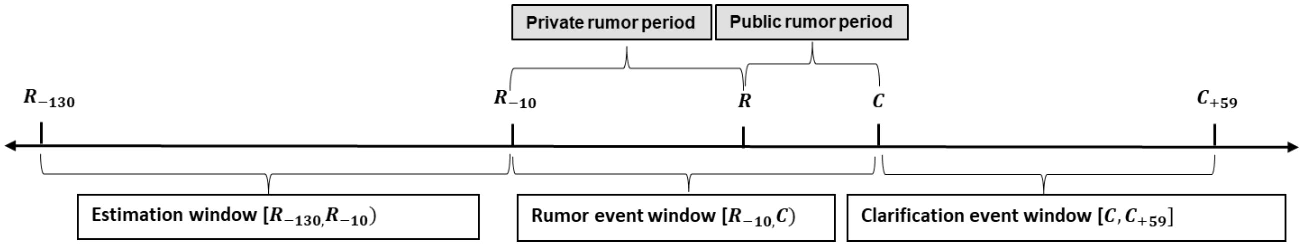


Figure 2: Rumor-Clarification Interval Days

This figure demonstrates the differing intervals between the emergence of rumors (R) and their subsequent clarifications (C). The variable lengths of the bars represent the range of time spans observed across different rumor clarification events within the study.

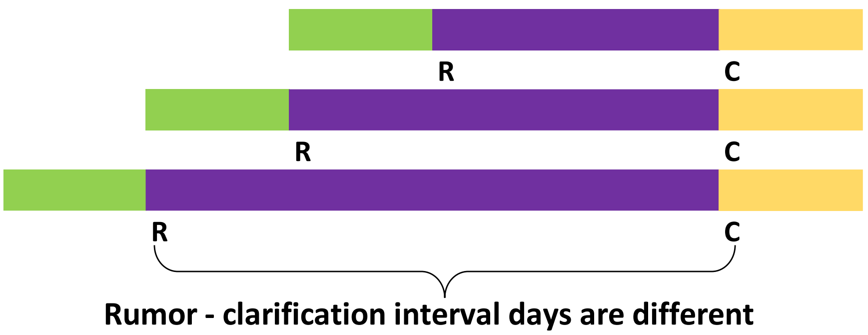


Figure 3: Abnormal Volatility

This figure compares average abnormal stock volatility across different rumor types, from 10 days before rumor releases to 60 days after clarifications. The line graph illustrates the average abnormal volatility, while the bar graph shows the corresponding non-parametric test statistics' t-values for True Positive, True Negative, False Positive, and False Negative rumors. The data suggests stock price reactions surrounding rumor and clarification events.[16]

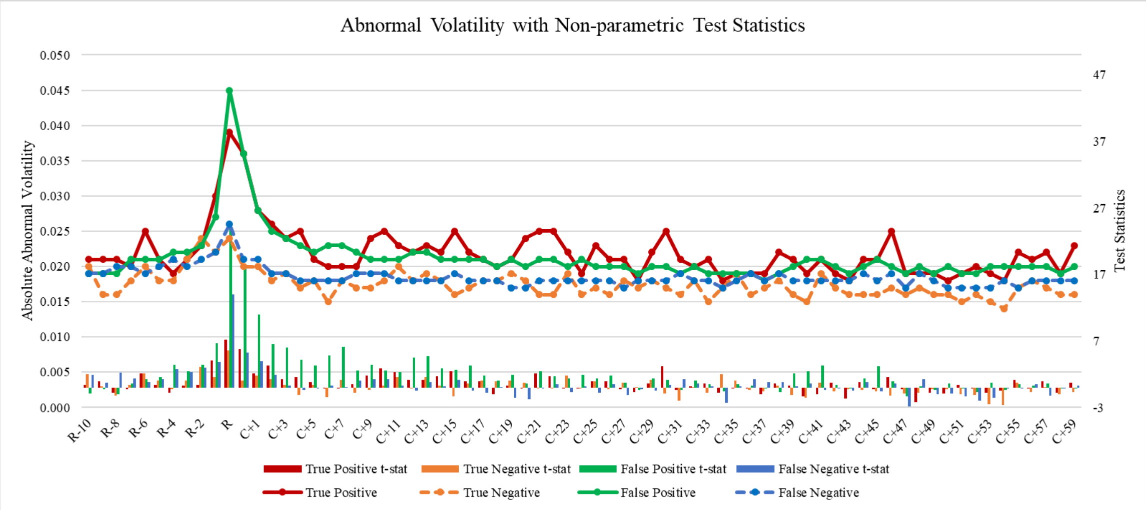
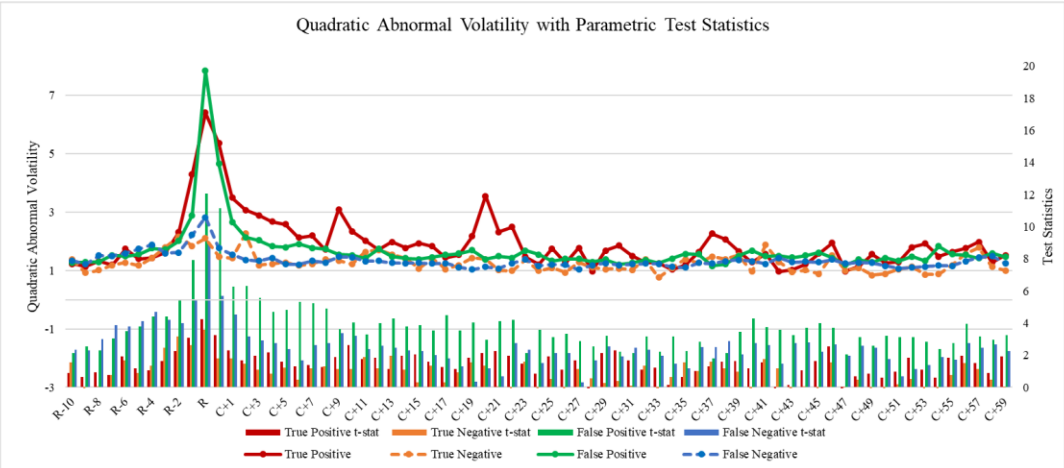


Figure 4: Quadratic Abnormal Volatility

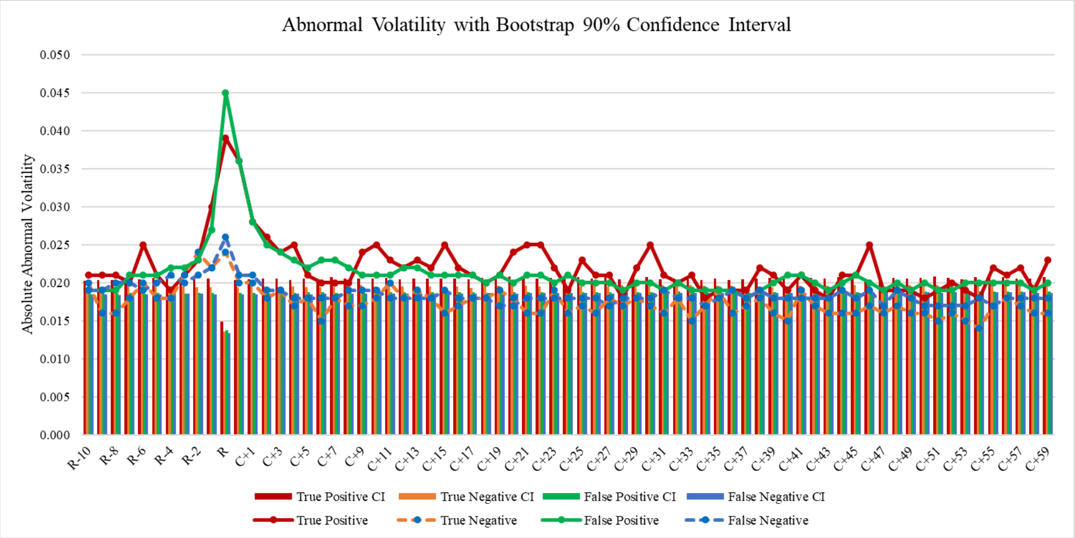
This figure presents the quadratic abnormal volatility across rumor types, covering the same period, from 10 days before rumor releases to 60 days post-clarification. The line chart shows average abnormal volatility levels, and the bars represent t-stat values for True Positive, True Negative, False Positive, and False Negative rumors.



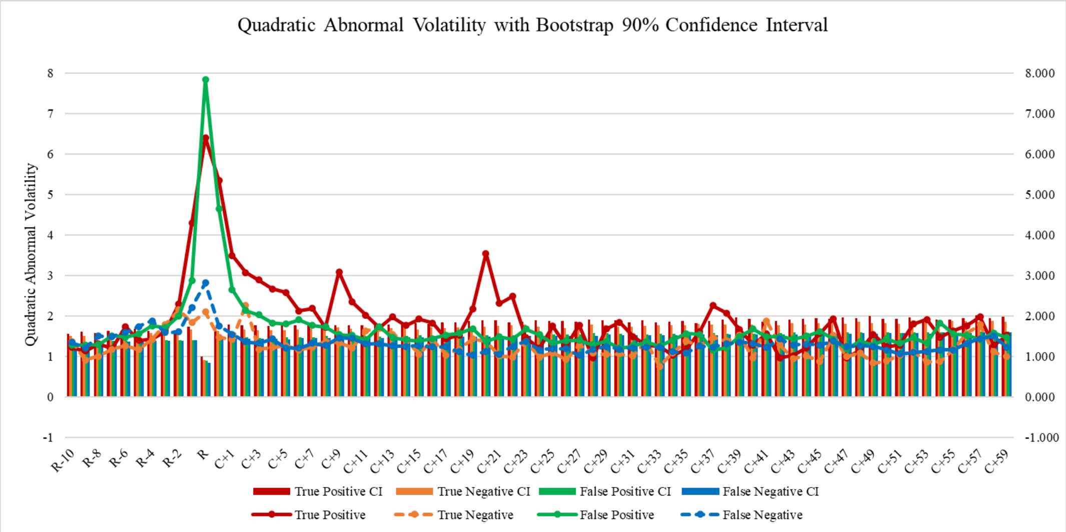
[16] To address the endogeneity issue of whether market movements drive rumors or rumors drive market movements, we extend the pre-event window to 60 days before rumor releases (see Appendix D). If spikes occur before the rumor release, this suggests that market movements are driving the rumors. While we cannot fully resolve the endogeneity concerns, our dataset is more reliable than previous studies, which often rely on proxies or theoretical models (e.g., Hirshleifer et al., 1994; Kadan et al., 2018; Van Bommel, 2003) .

Figure 5: Bootstrap Test

This figure shows average abnormal volatility from 1,000 simulations across 2,127 events, creating a distribution for the event window. It illustrates the 90% confidence interval thresholds used to calculate p-values for abnormal volatility, covering the period from 10 days before rumor releases to 60 days post-clarification.



This figure illustrates the quadratic abnormal volatility for different types of rumors, with 90% confidence interval thresholds from bootstrap simulations. The event window is from 10 days before rumor releases to 60 days post-clarification announcements.



Appendix 1: Variable Definition

Variable	Description
Size	Ln(Asset)
BTM	Natural Logarithm of Book Value of Equity / Market Cap
Mom	Momentum. Buy-and-hold return over estimation period
SOE	A dummy variable indicating state of enterprise
Short	A dummy variable indicating shortable stock
Lev	Liability/Asset
TobinQ	Market value of equity plus the difference between assets and common equity, scaled by total assets.
ROA	The ratio of a firm's net profit to total assets
Interval	The number of days between rumor release and clarification announcement, calculated by the clarification effective date – rumor effective date.
SocialMedia	A binary variable, 1 for rumors originally from social media, 0 for those from traditional media.
Neg	A binary variable, 1 for negative rumors, 0 for positive rumors.
TrueRumors	A dummy variable indicating that a rumor has been reported as genuine.
$AVOL_{[R]}$	We treat the period from rumor to clarification as a one-day abnormal volatility calculated as $\frac{1}{T}\sum_{t=1}^{T}\lvert AR_{i,t}\rvert$, where T is the interval length.
$CAVOL_{[R-10, R]}$	Cumulative abnormal volatility over a 10-day period preceding the release of the rumor and the abnormal volatility on rumor announcement day $AVOL_{[R]}$, averaged by the number of days in the period.[17]
$CAVOL_{[C, C+1]}$	Cumulative abnormal volatility over a short period (2 days) after the release of the clarification announcement and averaged by the number of days in the period.
$CAVOL_{[C, C+19]}$	Cumulative abnormal volatility over a 20-day period after the release of the clarification announcement and averaged by the number of days in the period.

[17] The CAVOL measure, averaged by the number of days in the period, aligns with Griffin et al., (2011). Note that multiplying and dividing by the number of days does not affect our conclusions.

Supplementary Appendix

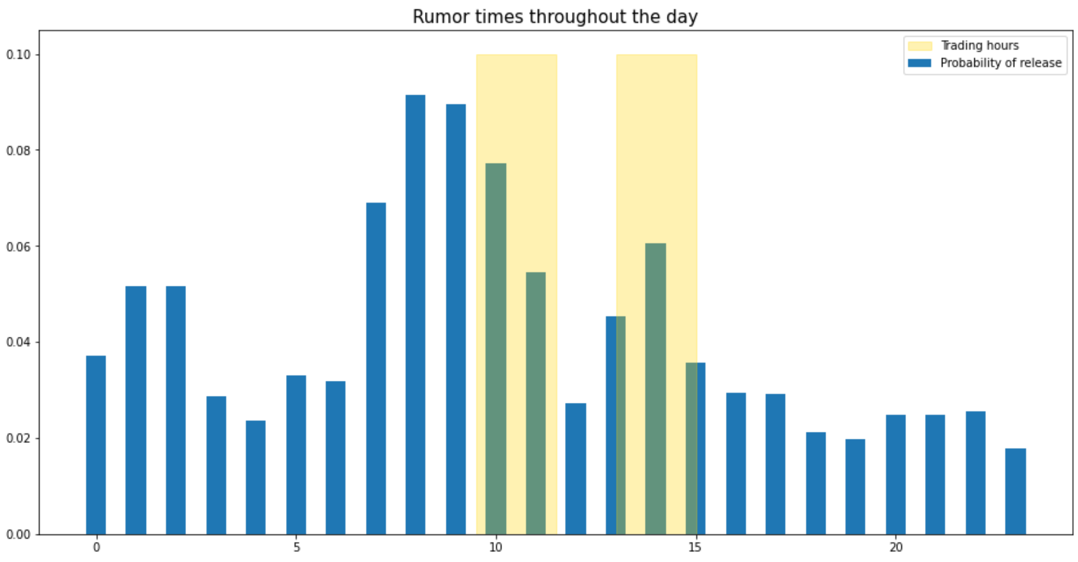
Appendix A: Release Timings for Rumor and Clarification

Appendix A1: Rumor and Clarification Effective Date

Rumors or clarifications released before or during trading hours can provoke instantaneous market reactions within the same trading day. Conversely, if this news made after market hours or on non-trading days, it would only affect stock prices on the subsequent trading day. This timing is crucial as it determines the actual effect of rumors and clarifications on stock price fluctuations. Therefore, we employ the effective date for rumors and clarifications instead of the real announcement date to measure the actual impact of these announcements when price movements occur. [18]

Figure A2: Rumor Time throughout the Day

This figure depicts the frequency of rumor releases at different times throughout the day. The blue bars represent the probability of rumors being released at any given hour, while the highlighted yellow sections indicate the official trading hours.



[18] Chang et al., (2007) and Danielsen & Sorescu (2001) adopt the effective date rather than announcement date to calculate the stock abnormal returns.

Figure A3: Rumor and Clarification Days throughout the Week

This figure compares the probability of rumor and clarification announcements across different days of the week. The top panel (c) shows the likelihood of rumors being released on each weekday, while the bottom panel (d) indicates the probability of clarification releases.

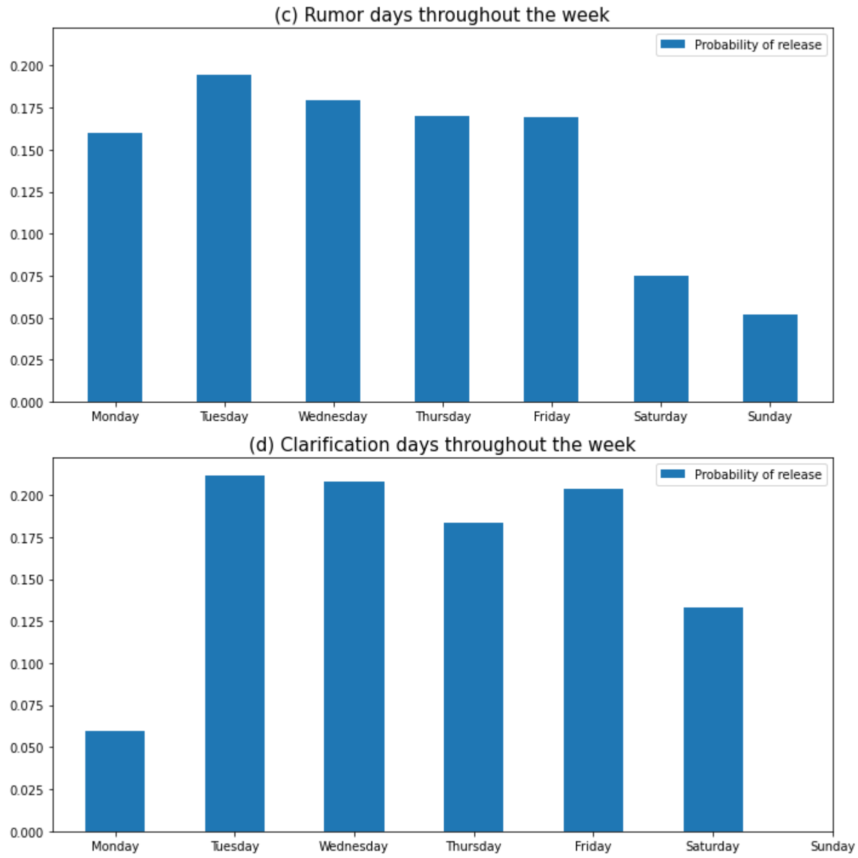
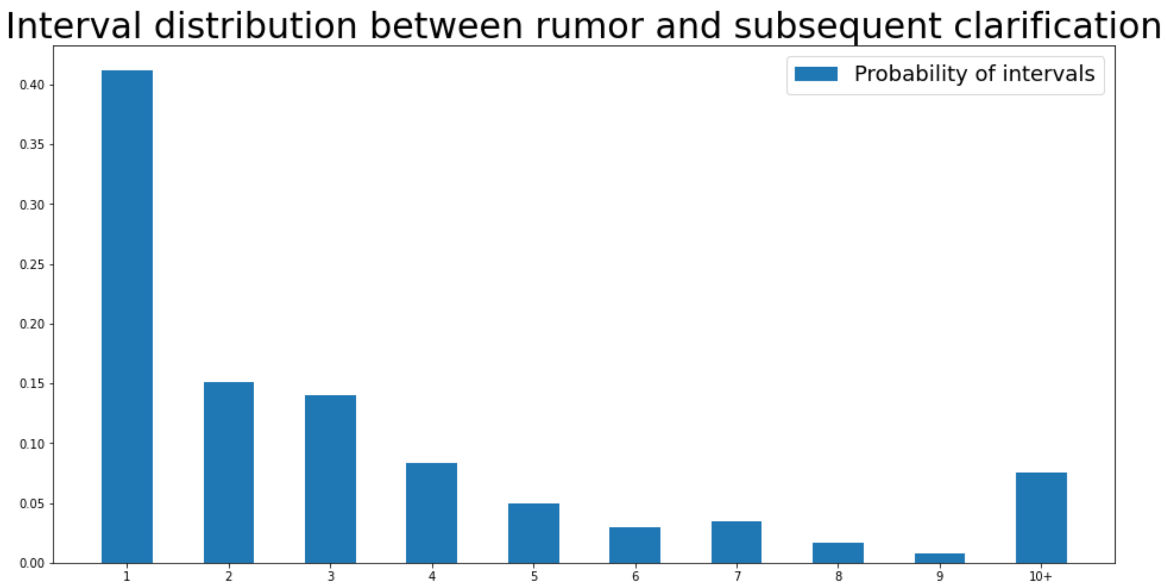


Figure A4: Interval Distribution

This figure illustrates the frequency distribution of the number of calendar days between a rumor's release and its subsequent clarification. The bars represent the probability of each interval, highlighting the most common timeframes for the market to address rumors.



Appendix B: Definition of Manually Collected Data

Our process starts with reviewing rumor-clarification pairs, forming the basis for simplified coding criteria. After our initial coding, a Finance PhD student independently reviews and recodes the data to ensure accuracy, with inconsistencies assessed using the kappa coefficient.[19] Subsequent discussions allow us to address these discrepancies, enhancing the reliability of this manually collected data. This method guarantees that our rumor-clarification pairs are assessed within a coherent and logical framework. A simplified representation of our coding approach is provided below for clarity.

[19] The kappa coefficient measures inter-rater reliability, indicating the level of agreement beyond what would be expected by chance. The kappa coefficient results are 92.36% for tone, 89.52% for veracity, and 90.17% for rumor type.

Appendix B1: Clarification Announcement Example (translated in English by ChatGPT)

证券代码：600833　　证券简称：第一医药　　公告编号：临 2010-001

上海第一医药股份有限公司
澄清公告

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一、传闻简述

2010 年 1 月 13 日，公司获悉《21 世纪经济报道》刊登题为《沪国资医药加速整合第一医药或划拨新上药》的署名报道。经公司书面征询控股股东及实际控制人百联集团有限公司后得到回复函，现就相关事项作出澄清。

二、澄清声明

经公司书面函证控股股东及实际控制人，控股股东及实际控制人回函明确表示：截至目前及未来三个月内，百联集团有限公司不存在有关媒体报道所述的涉及我公司的股权转让、非公开发行、债务重组、资产剥离等其他重大资产重组事项。

三、风险提示

公司郑重提醒广大投资者：《上海证券报》为公司指定的信息披露报刊，本公司发布的信息以在上述指定报刊刊登的公告为准，请广大投资者理性投资，注意风险。

上海第一医药股份有限公司
董　事　会
2010 年 1 月 14 日

Shanghai No.1 Pharmaceutical Co., Ltd. (Stock Code: 600833)
Clarification Announcement

The company's board of directors and all directors guarantee that the content of this announcement is free of any false records, misleading statements, or major omissions, and they bear individual and joint responsibility for the truthfulness, accuracy, and completeness of the content.

1. Rumor Description

On January 13, 2010, the company learned from "21st Century Business Herald" that an article titled "Shanghai Pharmaceutical Plans to Integrate Shanghai No.1 Pharmaceutical Co., Ltd." was published. The company immediately verified with its controlling shareholder, Baoneng Group Co., Ltd., and hereby clarifies the relevant matters.

2. Clarification Statement

After verification with the controlling shareholder, Baoneng Group Co., Ltd., the controlling shareholder confirmed that within the last three months, Baoneng Group Co., Ltd. has not negotiated or signed any agreement regarding the transfer of the company's shares with any media reports concerning the company's controlling shareholder. There have been no undisclosed significant events such as public offerings, debt restructuring, or major asset purchases and sales.

3. Risk Warning

The company reminds investors: "Shanghai Securities News" is the designated media for the company's information disclosure. The information published by the company shall prevail based on the announcements disclosed in "Shanghai Securities News." Investors are advised to make rational investment decisions and pay attention to investment risks.

Shanghai No.1 Pharmaceutical Co., Ltd.
Board of Directors
January 14, 2010

Appendix B2: Definition of Rumor Nature (Tonality)

Rumor Types	**Description**	**Effect**	**Example**
Positive Rumors	News that brings positive prospects for the company	Stock price is expected to increase	Public offering, good investment / cooperation /firm performance, turning losses into profit, and assets injection.
Negative Rumors	News that highlights potential problems or negative issues within the company	Stock price is expected to decline	Legal disputes, regulatory violations, concealment of important matters, and misleading statement.
Neutral Rumors	Information with unclear market implications, not distinctly good or bad	Stock price movement is uncertain	The rumor of replacing members of the board of directors by the shareholders' meeting of the company.

Positive Rumors spread news of potential success and growth within a company. This could be anything from promising investments, strong performance reports, or assets injection. These rumors suggest a bright future for the company, encouraging investors to buy more shares and driving stock prices up.

Negative Rumors bring to potential problems, such as legal issues, regulatory violations, financial distress, or operational setbacks. This type of information can shake investor confidence, leading to a drop in stock prices as investors sell off their shares to avoid potential losses.

Neutral Rumors are defined as information that has no clear market implications and does not distinctly convey good or bad news. Examples include potential changes in company leadership or the replacement of the board of directors. In the Chinese stock market, neutral rumors may arise from a lower risk of detection and penalties, as their vagueness often skirts strict regulatory standards. Market players might use these rumors to "test the waters," evaluating investor responses without making explicit assertions. Such rumors leave investors guessing about what's to come, causing uncertain stock price movements. These neutral rumors are excluded from our sample, as we focus only on clear-cut positive and negative rumors to maintain the precision of our analysis.

Appendix B3: Definition of Rumor Veracity

Rumor Veracity	**Description**	**Effect**	**Example**
True Rumor	Companies admit rumors	Stock price is expected to stabilize or move in the direction suggested by the initial rumor	A company admits an earnings profit rumor, leading to a stock price increase
False Rumors	Companies deny rumors	Stock price is expected to move in the opposite direction of the rumor sentiment	A company denies a bankruptcy rumor, resulting in a stock price recovery

True Rumors are those that companies confirm to be accurate. When a company admits to a rumor, the stock price is expected to stabilize or move in the direction suggested by the initial rumor. For example, if a company confirms a profitability rumor, it can lead to a stock price increase.

False Rumors are those that companies deny. When a company denies a rumor, the stock price is expected to move in the opposite direction of the initial rumor sentiment. For example, if a company denies a bankruptcy rumor, it may result in a stock price recovery.

Appendix B4: Definition of Rumor Type

Rumors Type	**Description**
Mergers and acquisitions	Mergers, acquisitions, buy-outs, and changes of ownership.
Asset reorganization	Asset injection, asset stripping, and restructuring.
Public offerings	Backdoor listings, equity carve-outs, and public offerings.
Corporate operations & performance	Business activities, investments, production, management, dividends, and equity incentives related to firm performance.
“Red alert”	Alleged violations of regulations, legal disputes, and arbitration.
Others	Fiscal policy, corporate leadership changes, and other events not easily categorized.

M&A involves significant changes within a company, such as mergers, acquisitions, or changes in ownership.

Example: When rumors circulate that Company B is acquiring Company A, Company A's stock price often rises as investors anticipate a premium, making this positive news for Company A. Conversely, Company B's stock may temporarily decline due to concerns over immediate financial costs, integration challenges, and potential debt. Thus, in the short term, this rumor is negative news for Company B. For long-term perspective, If rumors indicate that the acquisition will bring long-term synergies and growth, it is positive news for Company B.

Asset reorganization includes actions such as asset injection and stripping, marking a strategic attempt by companies to streamline operations and enhance financial health.

Example: If company A announces a divestiture plan to sell a lagging division, the immediate market reaction might be negative due to uncertainties about the company's financial stability (we define it as negative news for company A). However, if the reorganization is perceived as a strategic move to shed non-core assets and focus on profitable segments, it could be viewed positively, leading to a potential rise in the stock price. Another case is the asset injections, Company B, the beneficiary, often enjoys a stock price uplift, a response to renewed investor trust in its financial and operational prospects. However, Company A, initiating the asset transfer, might endure a brief dip in stock value, reflecting the immediate financial outlays, even though the move may offer long-term strategic gains.

Public offerings including strategies such as backdoor listings (listing a private company through a public one) and equity carve-outs (selling a portion of a subsidiary to the public), refer to the various methods a company employs to offer securities to the public.

Example: Speculation might arise that a well-known private company is planning an initial public offering (IPO). This rumor could spark investor interest, expecting the stock to increase in value post-offering. IPOs generally are perceived positively in China.

Corporate operations and performance include various business activities, investments, production processes, management practices, dividends, and equity incentives.

Example: If there's speculation about a company securing a significant contract, launching a groundbreaking product, expanding into new markets, dividends announcement, stocks might soar due to anticipated growth. Conversely, rumors about missed revenue targets, loss of key clients, or failed products can result in a sharp decline in stock prices.

Violation of Laws or Rules (**"Red Alert**") is usually associated with legal troubles or significant regulatory violations.

Example: If a company is rumored to be the subject of a government investigation or involved in a scandal, it's often met with a sell-off, plummeting the stock price due to fears of hefty fines, legal battles, or irreparable reputational damage. Generally, such “red alert” rumors are negative news for the parties implicated, such as for the defendant or those involved in the controversy. However, if Company A is the plaintiff and the rumor suggests a high likelihood of winning a lawsuit against Company B, the "Red Alert" rumor can positively impact Company A's stock price while negatively affecting Company B.

the "Others" includes diverse corporate events that do not fit into the standard classifications. This encompasses changes in fiscal policy, corporate leadership changes, macroeconomic factors, and other events not easily categorized.

Example: Positive rumors, for example, introducing an innovative equity incentive program would boost stock prices by signalling employee confidence and potential performance improvements. In contrast, unsettling rumors, such as unexpected CEO turnover or controversial new policies would be associated with stock price declines due to perceived instability or strategic ambiguity.

Appendix B5: Rumors During Stock Halts

We manually extract 3,515 rumor-clarification pairs, integrating them with daily market and individual stock data to confirm trading activities on the respective dates. This step is crucial because an inability to merge the rumor or clarification date with the daily market data indicated that, although the market is active (trading days), the stocks related to the rumor-clarification pairs shows no transactions, suggesting possible trading suspensions. Our sample reveals 618 such pairs that aligned with trading days but has no corresponding stock transactions.

We recheck of these 618 cases show that the nature of the rumors did not meet our established criteria for rumors with potential price impact. For instance, stock 300313 experiences a trading halt on 10 September 2020, due to an unprecedented surge over the preceding 12 trading days, prompting regulatory investigation. The rumor circulate during this period are speculative narratives attempting to justify the previous price increases, not factors influencing current market trends. Another common scenario prompting stock suspensions, as outlined in clarification announcements, involves significant corporate restructurings surrounded by substantial uncertainty. These announcements typically state that “to maintain transparent information disclosure, protect investor interests, and avert unusual stock price swings, company XXX would pause trading for a specified period.”

These inconsistencies were not unique but rather a consistent pattern among the 618 cases, all marks by similar trading suspension situations. We exclude these data from our sample to ensure our focus remains on rumors directly associated with price fluctuations.

Appendix C: Rumors and Clarifications Distribution

Confusion Matrix C1: Confusion Matrix (Distribution) of Rumors and Clarification

This confusion matrix categorizes rumors into true and false based on subsequent clarifications, breaking down the proportions of negative and positive rumors.

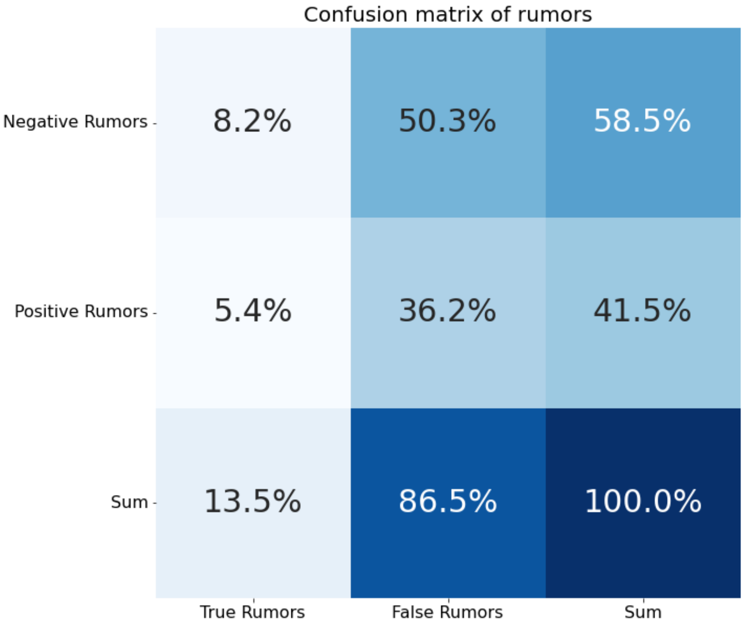


Table C2: Rumor Type by Market Cap

Large-cap companies attract the most market attention, accounting for 41.8% of total rumors, with false negatives being the most common (21.1%). Rumors increase with firm size, followed by medium-cap (31.5%) and small-cap firms (26.7%). False rumors, especially false positives for medium-cap and false negatives for small-cap, may reflect speculative efforts to influence less liquid stocks. Overall, negative rumors are more frequent than positive ones, and false rumors outnumber true rumors.

Rumor Type by Market Cap	True Positive Rumor	True Negative Rumor	False Positive Rumor	False Negative Rumor	**Total**
Small	1.3%	2.6%	9.6%	13.2%	26.7%
Medium	1.8%	2.6%	11.2%	16.0%	31.5%
Large	2.3%	3.1%	15.3%	21.1%	41.8%
Total	5.4%	8.2%	36.1%	50.3%	100.0%

Table C3: Rumor by Event Type

The Chinese market's sensitivity to the corporate operation and performance news, with a significant portion of rumors centered around this theme, making up 42.4% of the total, with false positive rumors leading at 18.9%.

These rumors may often stem from the public's high expectations for corporate growth and the market's speculative nature.

Rumor by Event Type	True Positive Rumor	True Negative Rumor	False Positive Rumor	False Negative Rumor	**Total**
M&A	0.2%	0.3%	3.5%	2.6%	6.6%
Asset Reorganization	0.5%	0.3%	8.4%	1.3%	10.4%
Public Offering	0.2%	0.3%	3.5%	1.3%	5.2%
Corporate Operation & Performance	4.1%	3.0%	19.2%	15.7%	41.9%
Red Alert	0.1%	2.5%	0.1%	24.6%	27.3%
Others	0.2%	1.9%	1.6%	4.9%	8.6%
Total	5.4%	8.2%	36.2%	50.3%	100.0%

Table C4: Rumor by Source

Traditional media (newspaper and TV) is the primary source of rumors, contributing to 52.1% of the total, with a significant lean towards false negative rumors at 27.9%. The high incidence of false negative rumors suggests a tendency towards sensationalism or perhaps a reflection of the regulatory landscape where bad news is swiftly and widely disseminated. The role of social media accounts for 47.9% of total rumors. Traditional media and social media contribute almost equally to the spread of rumors.

Rumor by Source	True Positive Rumor	True Negative Rumor	False Positive Rumor	False Negative Rumor	**Total**
Traditional Media	3.0%	4.2%	17.0%	27.9%	52.1%
Social Media	2.4%	3.9%	19.1%	22.4%	47.9%
Total	5.4%	8.2%	36.2%	50.3%	100.0%

Table C5: Rumor by Year

The annual spread of rumors highlights certain years with increased market activities or regulatory changes. For instance, the higher rumor incidences in 2009 and 2013 might correlate with market reactions to the global financial crisis and the Chinese government's subsequent economic measures.

The decrease in rumors post-2020 could be associated with several factors, including stricter market surveillance by Chinese authorities, the COVID-19 pandemic's market impact, or perhaps an evolving investor base becoming more discerning of unverified information.

Rumor by Year

Year	True Positive Rumor	True Negative Rumor	False Positive Rumor	False Negative Rumor	**Total**
2007	0.4%	0.1%	2.6%	1.4%	4.5%
2008	0.4%	0.4%	2.4%	3.5%	6.7%
2009	0.6%	0.6%	4.3%	2.6%	8.2%
2010	0.4%	0.3%	2.6%	2.9%	6.1%
2011	0.3%	0.4%	2.6%	3.9%	7.2%
2012	0.4%	0.6%	1.9%	4.8%	7.6%
2013	0.5%	0.6%	2.3%	5.7%	9.1%
2014	0.7%	0.3%	2.5%	4.7%	8.2%

2015	0.4%	0.6%	2.6%	3.1%	6.8%
2016	0.3%	0.8%	2.7%	3.3%	7.1%
2017	0.3%	0.9%	2.2%	4.3%	7.7%
2018	0.3%	0.8%	2.6%	3.4%	7.0%
2019	0.0%	0.9%	1.6%	3.0%	5.5%
2020	0.2%	0.5%	1.6%	1.7%	4.0%
2021	0.1%	0.1%	1.0%	1.1%	2.3%
2022	0.2%	0.2%	0.5%	1.1%	2.0%
Total	5.4%	8.2%	36.2%	50.3%	100.0%

Appendix D: Robustness Test

Figure D1: Abnormal Returns for Tone Validation

These charts illustrate the average abnormal returns of true rumor (top panel) and false rumors (bottom panel), categorized by positive and negative tones over the event window. It is used to validate the accuracy of tone classifications by examining whether positive (negative) tones align with positive (negative) abnormal returns around the rumor release date.

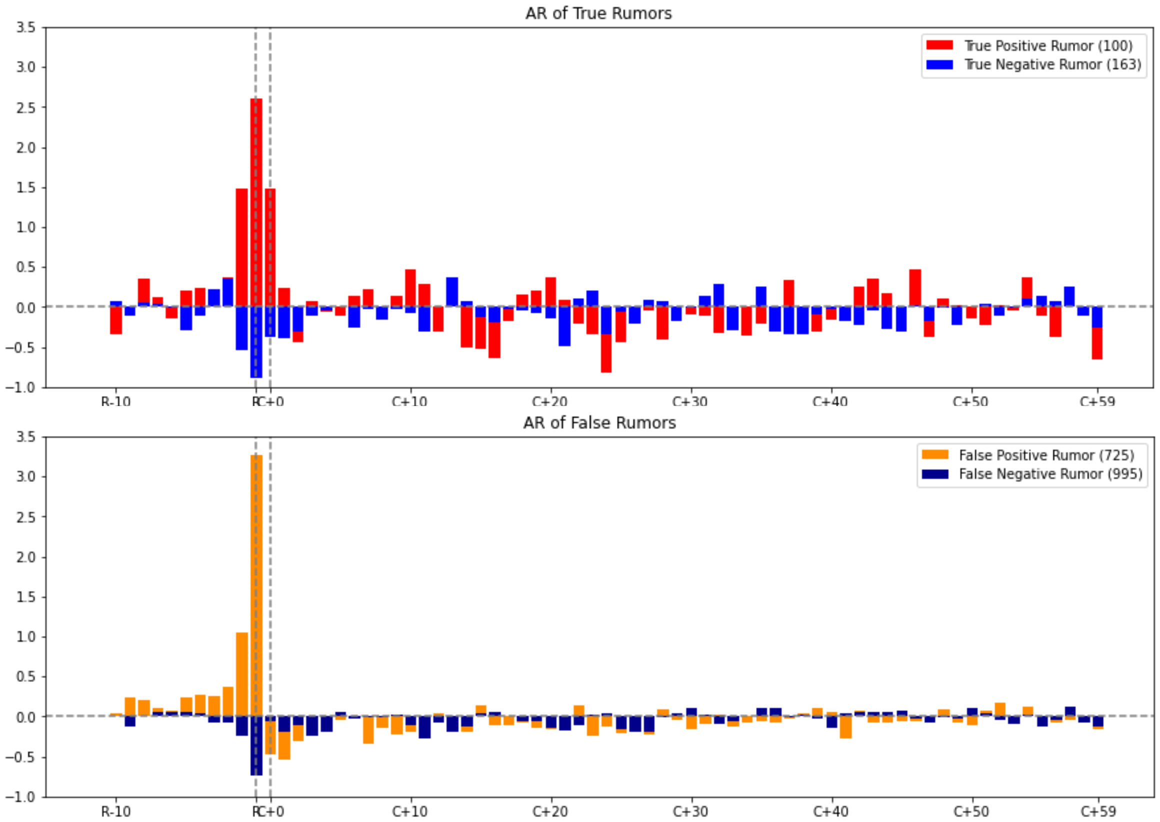
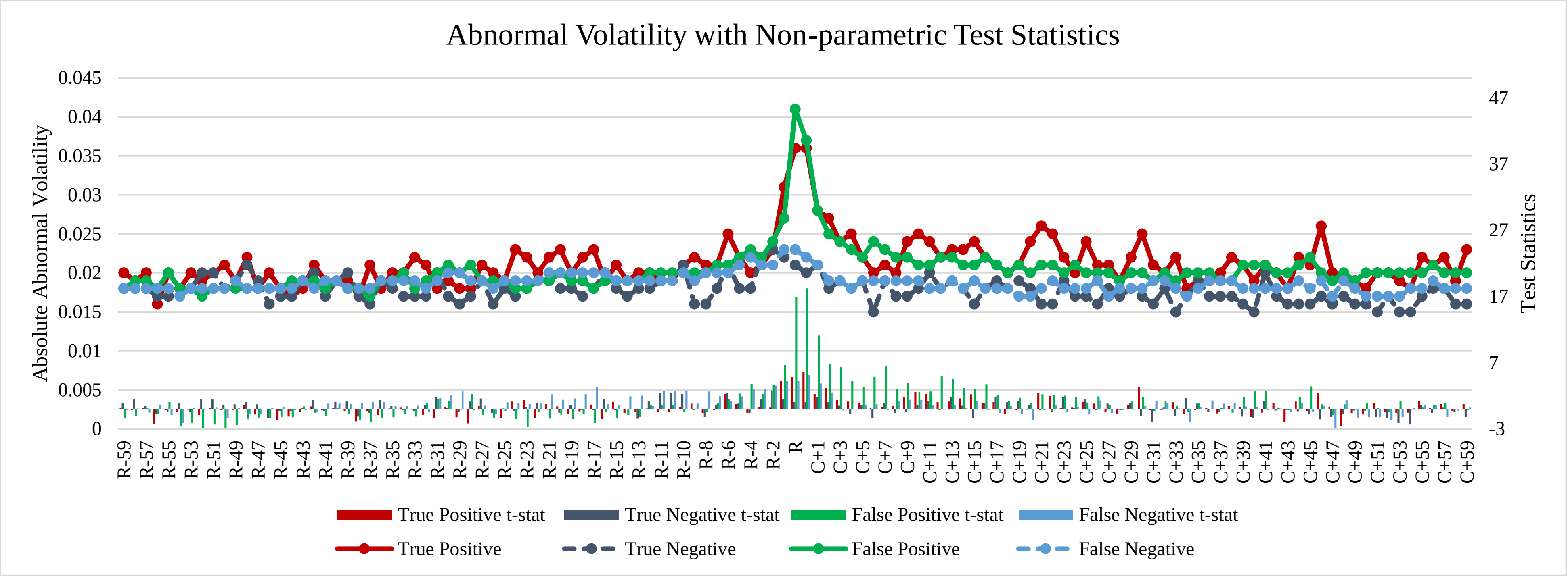


Figure D2: Abnormal Volatility Up to 60 Days Before Rumor Release

This figure shows average abnormal stock volatility across different rumor types, from 60 days before rumor releases to 60 days after clarifications. The line graph illustrates the average abnormal volatility, while the bar graph shows the corresponding non-parametric t-statistics for True Positive, True Negative, False Positive, and False Negative rumors. The data shows stock price reactions surrounding rumor and clarification events.



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