



When echoes surpass voices: Market reaction to forwarded news

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ARTICLE INFO

JEL classification:

G14
O16
N25

Keywords:

News types
News tone
Market reaction
Investor attention
Media credibility

ABSTRACT

We examine the impacts of two types of news, forwarded news and novel news, on market reactions and investor attention in the Chinese stock market. Surprisingly, we find that forwarded news evokes a stronger market reaction than novel news. To understand this phenomenon, we investigate and find three mechanisms through which forwarded news influences investor behavior: filtering, verification, and amplification effects. The filtering effect shows that forwarded news, having been selected for resharing, contains information content that has persistent effects on stock return. The verification effect indicates that forwarded news, particularly following scandals involving news platforms, is perceived as more credible, thus eliciting a stronger market reaction. The amplification effect shows that the redistribution of news magnifies its reach and captures investor attention, leading to increased investor search and trading on the stocks. Moreover, the impact of forwarded news on investor attention is more pronounced for firms with greater information opacity. Our results show the distinctive roles of forwarded news and novel news in the financial market, highlighting the importance of considering the heterogeneity of news information.

1. Introduction

In recent years, the rapid evolution of internet technologies has fueled an information revolution, altering the way investors access and process information. This transformation has led to significant shifts in the financial landscape, as news now disseminates more efficiently and exerts a more substantial influence on the financial market (Engelberg & Parsons, 2011). A debate persists regarding the influence of media coverage on capital markets, with some arguing that it conveys valuable information, resulting in a risk premium for certain stocks (Fang & Peress, 2009), while others contend that it only affects investor sentiment and attention, leading to stock price fluctuations without transmitting fundamental information (e.g., Barber & Odean, 2008; Tetlock, 2007; Tetlock, 2011). However, most literature focuses on the impact of aggregated news on the stock market, overlooking news heterogeneity.

In this paper, we aim to bridge this gap by examining the effects of novel news and forwarded news in the Chinese stock market. We define novel news as original content that is being introduced to the public for the first time and has not been previously disseminated or reported by other sources. Its novelty means it can significantly impact investor behavior by providing new insights and original information to the

market. Forwarded news refers to content that is redistributed content from existing sources, repeating information already in the public domain. While not original, its widespread dissemination can enhance the original news' impact, possibly influencing investor sentiment and behavior due to repeated exposure.

This paper consists of two parts. We first investigate how the market responds to both news types to assess market efficiency and the media's role in stock valuations. Next, we explore the mechanisms through which forwarded news affects investor behavior. We examine three key effects: the filtering effect, where news is forwarded because it is perceived as particularly relevant or important; the verification effect, where forwarding serves as an endorsement of the original news's credibility; and the amplification effect, which enhances the reach and impact of the original information.

We expand on Tetlock (2011), who investigates the market response to the staleness of news in the US market. In his paper, "news staleness" is calculated based on the news's textual similarity to previous news stories about the same firm. The focus is on the incremental information content of news (or the diminishing novelty of information). Unlike stale news, which involves rephrasing or recombining existing information, we define forwarded news as those explicitly marked as "forwarded

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<https://doi.org/10.1016/j.irfa.2024.103579>

Received 22 April 2024; Received in revised form 13 June 2024; Accepted 17 September 2024

Available online 20 September 2024

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from” and have over 90 % similarity to existing news. This distinction is crucial, as compared to stale news, forwarded news contains minimal new information, but rather a redistribution of old information. Our approach to focusing on forwarded news allows us to exclude the potential effects of any incremental information in the news. Moreover, stale news might involve recombination or reinterpretation of existing information. [Fedyk and Hodson \(2023\)](#) suggest even sophisticated investors have difficulty identifying old information that recombines content from multiple sources. The clear indication of “forwarded from” in forwarded news mitigates the concern that investors might overlook the lack of novelty. More importantly, the explicit forwarding tag signals to investors that the news has undergone a filtering and verification process by other platforms, potentially amplifying these effects in comparison to stale news.

In the first part of our analysis, we examine whether and how the financial market responds to forwarded and novel news, categorized by positive or negative tone. We first compare the market response by event study and find that the stock market reacts differently to the two types of news. The average CAR around the novel news release window is not statistically significant, suggesting that investors may under-react to novel news. In contrast, we find a significant market reaction towards forwarded news. In addition to event study, we employ regression method, which allows us to control for potential factors that could influence both media coverage and market reaction. Consistent with the event study, we find that forwarded news tone has a positive and significant impact on market reaction while novel news does not. The difference in coefficients of the two types of news is statistically significant, highlighting the distinctive impacts of forwarded and novel news. To address potential endogeneity issues, such as reverse causality and selection bias, we conduct robustness checks using both an instrumental variable approach and propensity score matching and the results remain similar ([Rosenbaum & Rubin, 1983](#); [Staiger & Stock, 1997](#)).

In the second part, we examine three potential mechanisms through which forwarded news affects market reaction: filtering effect, verification effect and amplification effect. The filtering effect refers to the process where only certain news stories, deemed important or relevant, are shared by other platforms. This selective sharing process helps investors to manage the overwhelming information flow. To determine whether the market reaction to forwarded news is due to fundamental information, we constructed long-short portfolios based on news tone. The significant positive alpha from the forwarded news portfolio, persisting for up to three months, confirms that forwarded news contains fundamental information. In contrast, we find that the alpha is not significant for novel news portfolios, suggesting that novel news, which has not been filtered through other media platforms, may not always contain significant information content. To investigate whether our results are simply due to that novel news being forwarded is more important (i.e., whether the filtering effect explains the whole story), we repeated the event study, including only news published on days without other events in the $[-5, +5]$ window. The significant market reaction to forwarded news persisted, suggesting that the impact is not solely due to the informational value of novel news but also other mechanisms at play.

We next examine the verification effect. Using the 21st Century Business Herald scandal in 2014 as an exogenous shock on investors’ trust in news media, we find that forwarded news, which is seen as more credible due to its endorsement through sharing, shows a greater impact on CAR after the scandal, indicating a heightened verification effect. In contrast, we do not observe similar changes in impact from novel news, confirming that the credibility of forwarded news significantly influences market reactions, especially after the trust crisis.

To examine the amplification effect, the third mechanism, we investigate how forwarded news and novel news influence investor attention using the Baidu search index as a proxy. The results of the event study and regression analysis show that investors respond to forwarded news by actively searching for information on Baidu, while there is no increase in search activity during the novel news window after

controlling for other variables. The results indicate that investors are more attentive to forwarded news than to novel news. Using trading volume as an alternative proxy for investor attention yields similar inferences. We further find that the positive association between forwarded news and investor attention is more pronounced in firms with poor information environments. This can be attributed to cognitive biases and heuristics, such as the availability heuristic, which leads individuals to rely on readily accessible information when making judgments ([Kahneman, 1973](#); [Tversky & Kahneman, 1973](#)).

Our study contributes to the literature in the following aspects. First, our study is among the first to compare the heterogeneity of news by differentiating between novel news and forwarded news. We build on [Tetlock \(2011\)](#), who examines market responses to stale news in the US, and find that the market reacts less to stale news (also see [Huberman & Regev, 2001](#); [Gilbert et al., 2012](#)). Unlike stale news, forwarded news in our study is a cleaner measure with minimal incremental information, allowing us to focus on the effect of forwarding behavior. We observe a stronger market reaction to forwarded news than to novel news in the Chinese stock market, which is likely due to the unique characteristics of the Chinese market as discussed in Section 2.

Second, we contribute to the literature by uncovering three mechanisms through which forwarded news influences investor behavior. The filtering effect confirms that forwarded news contains fundamental information relevant to investors’ decisions while novel news might not. This reconciles the debate on media informativeness in prior literature. While some studies find that media news contains noise and affects investor sentiment without transmitting fundamental information (e.g., [Barber & Odean, 2008](#); [Tetlock, 2007](#); [Tetlock, 2011](#)), other studies show that media news conveys valuable information. For example, [Tetlock et al. \(2008\)](#) find that the negative words in firm-specific news can be used to predict individual firms’ accounting earnings and stock returns. [Huang and Zhang \(2022\)](#) find that industry-level media tone contains fundamental information. [Ahmad et al. \(2016\)](#) find that negative media tone impacts firm-level returns, with some effects quickly reversed while others endure. This implies that media news can be both sentiment (or noise) and value-relevant information, and efficiently functioning markets can eventually discriminate between them. However, prior literature does not explain why these effects coexist, as it examines news in aggregate without considering news heterogeneity. Our study complements these findings by demonstrating the filtering effect of forwarded news, where only news perceived as relevant or important is reshared. This mechanism illustrates how media aids in identifying and amplifying news with significant information content, thereby enhancing market efficiency.

Considering the ongoing concerns about news quality in China’s media industry, our findings on the verification effect propose that peer media platforms might act as a disciplinary role of news quality as investors tend to cross-verify the news across different platforms. [You et al. \(2018\)](#) and [Ding et al. \(2018\)](#) find that articles by market-oriented media have higher quality compared to articles by state-owned media. Our work extends their findings by showing that forwarded news also offers a more trustworthy news source.

To test the amplification effect, our study diverges from prior literature that indirectly infers investor attention to stale news through the association between news and market returns (e.g., [Tetlock, 2011](#)). Instead, we examine investors’ trading and searching behavior, providing direct evidence of the role forwarded news plays in shaping stock prices and investor attention processes.

Last, our study adds to the literature on two primary theories: the Efficient Market Hypothesis (EMH) and behavioral finance. The EMH posits that stock prices fully incorporate all publicly available information, including media coverage, assuming rational market participants ([Fama, 1970](#); [Grossman & Stiglitz, 1980](#)). Behavioral finance, however, argues that investors are influenced by limited attention, emotions, and biases, leading to decisions based on attention-catching stocks rather than objective information ([Barber & Odean, 2008](#);

Frank & Sanati, 2018). Our findings support the EMH by showing market reactions to news with substantive information content. They also align with behavioral finance, as forwarded news, despite lacking novel information, still significantly impacts the market. This suggests that cognitive biases, such as limited attention, can lead investors to overreact or under-react to certain news pieces.

The remainder of this paper is organized as follows. The next section covers the literature and hypothesis development. Section 3 introduces the dataset and sample construction. Empirical findings on baseline regressions and underlying mechanisms are outlined and discussed in Sections 4 and 5. Section 6 concludes.

2. Related literature and hypothesis development

The effects of media coverage on capital markets have been a subject of interest for researchers, as media plays a critical role in disseminating firms' information and shaping investor perceptions. Media coverage improves the information environment by making information accessible to a broad range of investors, leading to better-informed decision-making and a more efficient financial market (Ding et al., 2020). An efficient market is characterized by the timely incorporation of new information into stock prices, which is facilitated by media coverage (Fang & Peress, 2009). Another important role of media coverage is to mitigate stock price crashes by uncovering negative news about firms, prompting corrective actions and improving corporate governance (An et al., 2020). Additionally, media acts as a corporate monitor, providing crucial information intermediary services for corporate governance (Kim et al., 2019; You et al., 2018). Regardless of whether the media coverage contains new information or not, it helps to reduce information friction (Fang & Peress, 2009).

However, it is essential to acknowledge that media coverage can also lead to information asymmetry and market inefficiencies due to biased reporting or selective dissemination of information (An et al., 2020; Core et al., 2008). Media outlets may exaggerate news content to capture investors' attention, or firms with poor performance might bribe media outlets for positive coverage, exacerbating information asymmetry and market distortions (Ahern & Sosyura, 2015). Behavioral finance theory contends that investors, constrained by bounded rationality, are susceptible to limited attention, emotions, and biases, leading them to base investment decisions on attention-catching stocks rather than objective financial information (Barber & Odean, 2008). For instance, Frank and Sanati (2018) demonstrate that negative media tone can lead to temporary stock price declines, while Barber and Odean (2008) emphasize the role of individual investors' attention in driving stock prices. This suggests that attention-grabbing news may experience higher trading volumes and price changes not necessarily aligned with their fundamental values. Additionally, the limited attention theory posits that when investors are presented with excessive information, cognitive biases can cause them to struggle in processing and differentiating between relevant and irrelevant data (Hirshleifer et al., 2009; S. Huang et al., 2019). This can lead to market reactions that deviate from the efficient market hypothesis (Huberman & Regev, 2001), such as over-reactions, particularly to old news (Gilbert et al., 2012; Tetlock, 2011). Fedyk and Hodson (2023) attribute this to "correlation neglect", where decision-makers fail to fully account for correlations across signals, a unique manifestation of limited attention (DeMarzo et al., 2003; Ortoleva & Snowberg, 2015). In this context, forwarded news emerges as an important factor to consider. Although forwarded news does not contain new information, it has the potential to generate a stronger market reaction than novel news.

Based on the theories from media and communication research and behavioral finance, we propose three possible reasons why forwarded news could exert greater influence: filtering effect, verification effect and amplification effect.

First, forwarded news has undergone a preliminary selection or vetting process by other news outlets, implying an inherent level of

importance or information content ("filtering effect"). This can be explained by the Gatekeeping theory from media and communication research, which posits that the media, including editors and news organizations, act as the gatekeeper, filtering valuable news and passing it to the public (Lewin, 1943; Shoemaker & Vos, 2009).

Second, when news is forwarded, it may undergo a process of social verification where repeated forwarding serves as an endorsement of its credibility ("verification effect"). This effect is more pronounced when reputable sources forward the news, according to source credibility theory (Hovland & Weiss, 1951). The act of forwarding can signal importance and reliability to investors, while the signaling effect can be less pronounced with novel news, which has not yet been subjected to widespread scrutiny or endorsement. Additionally, investors could be subject to conservatism bias, which suggests they are inherently resistant to changing their beliefs based on new information. Forwarded news, having passed through the filtering and verification process, is more readily accepted by investors (Barberis et al., 1998; Edwards, 1968).

Third, forwarded news gets amplified as it is shared across networks, increasing its visibility and perceived importance. This widespread dissemination captures investor attention more effectively, particularly for those with limited attention (Huberman & Regev, 2001; Tetlock, 2011), leading to increased search activity and trading volumes for the stocks mentioned. Additionally, extensively shared forwarded news can trigger herding behavior, leading to a more substantial market reaction as investors collectively follow the perceived wisdom of the crowd (Bikhchandani et al., 1992).

Collectively, we hypothesize that compared to novel news, forwarded news can trigger a greater market response (*Informative Forwarded News Hypothesis*).

Our study focuses on the Chinese stock market, as we expect the above-mentioned impacts of forwarded news can be more pronounced in the Chinese stock market compared to more mature markets such as the US market for several reasons. First, media news plays a more important role in disseminating information in the Chinese stock market. The Chinese market is characterized by a higher proportion of retail investors, with retail investors making up about 80 % of the market compared to 20 % in the US. Institutional investors have various channels to access company information, such as corporate site visits, roadshows, private meetings, and professional platforms like Bloomberg, WIND, and CSMAR, as well as sell-side analyst reports providing timely updates on company and industry information (Bowen et al., 2018; Chen et al., 2020; Cheng et al., 2016, 2019; Jiang & Yuan, 2018). In contrast, retail investors lack these resources and rely more heavily on news media for information.

Second, investors may react less to novel news in the Chinese stock market because the regulatory environment, heavily influenced by government entities like the China Securities Regulatory Commission (CSRC), often results in slower dissemination of novel news. Market participants tend to wait for official verification or guidance before reacting, leading to a delayed response to novel information.

The filtering effect of forwarded news can be stronger in the Chinese market. Emerging markets such as China have a high proportion of individual investors who engage in speculative trading (Liu et al., 2019; Stambaugh & Yuan, 2017), creating an environment where rumors and speculative news can have an outsized impact. Compared to institutional investors, who have sophisticated experts to judge the importance or relevance of the news, retail investors lack these resources and abilities, making them more reliant on mechanisms such as other news platforms to filter out noise. Additionally, the quality of media in China varies significantly, with a mix of state-controlled outlets and less regulated online platforms. This variability makes the filtering effect of forwarded news more pronounced, as the selective re-sharing process helps filter out low-quality news. This selective process signals to retail investors that the forwarded news is more relevant or important.

The verification effect in the Chinese stock market could be

particularly pronounced due to the compromised credibility of the media and frequent financial scandals. Incidents like the 21st Century Business Herald scandal have led to widespread skepticism among investors, who doubt the reliability of novel news due to prevalent paid and fake news practices (You et al., 2018). Furthermore, pervasive accounting scandals, insider trading, and corruption have significantly eroded investor confidence in new information (Cumming et al., 2015). Consequently, investors are more inclined to cross-check information across various platforms, enhancing the impact of forwarded news, which they perceive as more credible due to its endorsement through sharing.

Last, the amplification effects of forwarded news can be more salient in the Chinese market due to the high level of retail investor participation, who exhibit herding behavior to attention-grabbing news, and are heavily influenced by social networks and media. Additionally, retail investors' constraints on time and resources make them more susceptible to limited attention bias. This makes them more influenced by the repeated exposure of forwarded news.

3. Sample and variable construction

3.1. Sample construction

We obtain the data from the China Stock Market and Accounting Research (CSMAR) database, which consists of all A-shares listed on both the Shanghai and Shenzhen Stock Exchanges from 2010 to 2019. To ensure the reliability and validity of our analysis, we apply several criteria to refine the dataset. First, we exclude stocks that have been listed for less than two years, as their limited trading history may not provide a sufficient basis for reliable analysis. Second, we eliminate stocks designated as special treatment (ST*) due to their predisposition for extreme returns, which may distort the overall assessment of the dataset. We also exclude financial and banking firms from our sample, as they are subject to unique regulatory frameworks. We further remove observations with missing control variables or stock return data. Last, to minimize the impact of potential outliers, all continuous variables are winsorized at the top and bottom 1 % level.

3.2. Media coverage and measuring news types

We compile news articles from 2010 to 2019 because online news adoption in China was not widespread before this period, and media coverage and forwarded news data for earlier years are not available in accessible databases.¹ To avoid potential ambiguity from multiple meanings or similar abbreviations in stock names, we use stock tickers as keywords when searching for news articles related to specific stocks. The media coverage data used in this study is collected from two sources: the first encompasses seven prominent Chinese online financial news platforms, and the second comprises the *Chinese Financial Press (China Daily)*. The selected media outlets, including *China Security Journal*, *Shanghai Security News*, *Securities Daily*, *21st Century Business Herald*, *China Economic Times*, *Financial News*, and *China Business News*, which are widely followed by investors and serve as their primary sources of information.

To focus on price-relevant information, we retain news with keywords such as “profit, earnings, interest, revenue, bullish, bearish, performance, annual/quarterly report, price prediction,” among others, in our analysis. A covered firm is defined as a company mentioned more

¹ Upon careful examining media coverage in China, it becomes clear that numerous outlets shifted their focus to pandemic-related reporting at the expense of detailed coverage on individual firms. Therefore, we exclude data from 2020 and beyond to account for the considerable disruptions to both media operations and stock market behaviors in China, resulting from the pandemic's impact.

frequently than others within a given article, ensuring a more coherent and rigorous analysis of the media's impact on specific firms.

To differentiate between forwarded news articles and novel news articles, we use the Vector Space Model (VSM) to calculate similarity scores among news articles featured by these media outlets mentioned above applied by previous studies (Salton, 1983; Tetlock, 2011). Specifically, we classify news articles labeled as “forwarded from...” and designate those with a similarity score exceeding 90 % as forwarded news. This threshold is set below 100 % to account for the possibility that identical news articles may be reported by different media outlets at varying times, thereby ensuring a more accurate classification. Novel news refers to articles with a substantially lower similarity score compared to previously published news stories, indicating that the content is being disseminated for the first time.

3.3. Measuring news tone

Prior studies employ different methods to categorize news tone. Some utilize the General Inquirer (GI) and Harvard IV-4 dictionary (e.g., Loughran & Mcdonald, 2011), while others rely on return signs on news days to distinguish between good and bad news (Engelberg et al., 2012; M. Z. Frank & Sanati, 2018; Ma et al., 2021). In this study, we use a well-documented dictionary (Loughran & Mcdonald, 2011; You et al., 2018) to determine whether news articles convey positive, neutral, or negative tones. This approach is necessary due to the unavailability of the Harvard IV-4 dictionary in China and discrepancies in the financial meanings attributed to specific English words. The SVM evaluates the frequency of positive and negative words in each article to classify the tone. The identification of news tone follows the procedure outlined below:

$$News\ tone_{i,t} = \frac{words^{positive} - words^{negative}}{Allwords}$$

$words^{positive}$ and represent the counts of positive and negative words, respectively. Positive and negative news are classified based on the percentage of positive and negative words using a well-documented dictionary (Loughran & Mcdonald, 2011; You et al., 2018). Specifically, we define news as “positive news” if the ratio of the difference between positive words and negative words to the total number of words in a news article exceeds 0, and as “negative news” if the ratio is less than 0.

3.4. Measuring stock market reaction: Cumulative abnormal return (CAR)

To assess the market reaction to news events, we employ the Cumulative Abnormal Return (CAR) as a measure, which is calculated based on the abnormal return in response to positive and negative forwarded/novel news. We set the estimation window as [-63,-5] (Frank & Sanati, 2018). Firms with fewer than 59 trading days of return data in the estimation window are excluded from the sample. For each firm i , we compute the abnormal returns using the market model. Formally, we estimate the follows:

$$R_{i,t} = a_i + b_i R_{m,t} + \mu_{i,t}$$

where $R_{i,t}$ represents the daily return on the stock of company i on day t , and $R_{m,t}$ denotes daily market return, and $\mu_{i,t}$ is the residual.

The abnormal daily return ($AR_{i,t}$) of firm i on day t , is then calculated as follows:

$$AR_{i,t} = R_{i,t} - (\hat{a}_i + \hat{b}_i R_{m,t})$$

where \hat{a}_i , \hat{b}_i are the estimated coefficients from the CAPM model regression. Finally, to evaluate both short- and long-term price re-

actions to forwarded (novel) news shocks, we apply various event windows and calculate the Cumulative Abnormal Return (CAR) as:

$$CAR_{i,t} = \sum_{t=-5}^n AR_{i,t}$$

By calculating CAR, we can effectively measure the market reaction to news events, providing valuable insights into the relationship between media coverage and stock price fluctuations. This comprehensive analysis allows us to better understand the impact of news tone on market outcomes.

3.5. Measuring investors' attention

Next, we measure daily firm-level investor attention using search volume data from the Baidu Index, a well-established proxy for investor attention in the Chinese market (e.g., Wen et al., 2019). As a robustness check, we use abnormal trading volume, a widely validated measure of investor attention (Barber & Odean, 2008; Ma et al., 2021). Following M. Z. Frank and Sanati (2018), we calculate the daily abnormal searching (or trading) volume by first calculating the realized searching (or trading) volume on a given day and taking its natural logarithm. We then determine the normal searching (or trading) volume for the same day by calculating the median value of the searching (or trading) volume over the previous two months (equivalent to 40 trading days). This period provides a reasonable sample size to establish a stable baseline while remaining responsive to recent trends. The daily firm-level abnormal searching (or trading) volume is calculated as the difference between the natural logarithm of realized searching (or trading) volume for each day and the natural logarithm of normal searching (or trading) volume. This difference represents the deviation of observed activity from expected levels.

The equation for daily abnormal searching volume is as follows,

$$\log_SVI_{i,t} = \log(\text{Searching Volume}_{i,t}) - \log\left(\text{Median}\left(\text{Searching Volume}_{i,t-1}, \dots, \text{Searching Volume}_{i,t-40}\right)\right).$$

where $\log_SVI_{i,t}$ denotes the natural logarithm of daily abnormal Baidu searching volume for stock i on day t . We calculate the value by subtracting the natural logarithm of the median searching volume for the previous 40 trading days ($[t-40, t-1]$) from the natural logarithm of the realized searching volume on day t .

The equation for daily abnormal trading volume:

$$\log_ATV_{i,t} = \log(\text{Trading Volume}_{i,t}) - \log\left(\text{Median}\left(\text{Trading Volume}_{i,t-1}, \dots, \text{Trading Volume}_{i,t-40}\right)\right).$$

where $\log_ATV_{i,t}$ denotes the natural logarithm of daily abnormal trading volume for stock i on day t . Similar to the previous equation, we calculate this value by subtracting the natural logarithm of the median trading volume for the previous 40 trading days ($[t-40, t-1]$) from the natural logarithm of the realized trading volume on day t .

3.6. Summary statistics

Table 1 presents summary statistics of the variables used in the main analysis, with detailed explanations provided in Appendix A. Notably, there is no significant difference between the number and tone of forwarded and novel news. However, the high standard deviation suggests

Table 1
Summary statistics.

| Variable | N | Mean | SD | P25 | P50 | P75 |
|---|--------|--------|-------|--------|--------|--------|
| <i>F_ntone</i> | 25,681 | 0.118 | 0.301 | -0.067 | 0.141 | 0.323 |
| <i>N_ntone</i> | 25,681 | 0.170 | 0.215 | 0.038 | 0.182 | 0.316 |
| <i>ln_nF_n</i> | 30,128 | 2.994 | 1.610 | 2.079 | 3.219 | 4.094 |
| <i>ln_nN_n</i> | 30,128 | 2.527 | 1.229 | 1.946 | 2.708 | 3.296 |
| <i>CAR</i> | 30,128 | 0.004 | 0.023 | -0.004 | 0.002 | 0.008 |
| <i>log_nATV</i> | 30,128 | 0.659 | 0.550 | 0.357 | 0.546 | 0.802 |
| <i>log_nSVI</i> | 11,493 | 4.920 | 1.478 | 4.963 | 5.220 | 5.541 |
| <i>Size</i> | 30,128 | 22.124 | 1.292 | 21.189 | 21.939 | 22.857 |
| <i>MB</i> | 30,128 | 2.194 | 2.131 | 0.853 | 1.567 | 2.760 |
| <i>Lev</i> | 30,128 | 0.422 | 0.211 | 0.251 | 0.413 | 0.580 |
| <i>ROA</i> | 30,128 | 0.041 | 0.069 | 0.015 | 0.040 | 0.073 |
| <i>Big4</i> | 30,128 | 0.057 | 0.231 | 0.000 | 0.000 | 0.000 |
| <i>Opaqueness</i> | 28,256 | 0.060 | 0.064 | 0.018 | 0.041 | 0.078 |
| <i>SYN</i> | 30,126 | -0.295 | 0.865 | -0.826 | -0.243 | 0.298 |
| <i>INST</i> | 30,078 | 0.378 | 0.237 | 0.173 | 0.383 | 0.565 |
| <i>ln_nInd_nF_n</i> | 30,128 | 8.308 | 1.396 | 7.399 | 8.590 | 9.380 |
| <i>ln_nAD_nfee</i> | 30,128 | 18.773 | 1.191 | 17.956 | 18.631 | 19.437 |
| <i>Ind_nF_ntone</i> | 25,670 | 0.117 | 0.094 | 0.069 | 0.121 | 0.179 |

This table presents the summary statistics for the variables used in the main analysis. Refer to Appendix A for descriptions of the variables.

considerable variation in news coverage and tones among firms. Investor attention, denoted by \log_SVI (natural logarithm of abnormal Baidu search volume) and \log_ATV (natural logarithm of abnormal trading volume), and market reaction (CAR) exhibit high standard deviations compared to the means. This indicates that news shocks prompt significantly different reactions in the market.

4. Market response to news shock: Empirical results

In this section, we explore the market's reaction to four types of news shocks, categorized by forwarded and novel news, as well as positive and

negative tones. Specifically, we examine the *Informative Forwarded News Hypothesis*, which posits that forwarded news has a greater price impact compared to novel news.

4.1. Event study: Cumulative abnormal return

We use the event study method to examine how the stock market responds to the firm-specific forwarded and novel news, respectively.

We define a "positive forwarded news day" as a day with no novel news, only forwarded news from specific firm, and where the average tone of the forwarded news is positive. Conversely, a "negative forwarded news day" is when there is no novel news, only forwarded news, and the tone of the forwarded news is negative. We apply a consistent classification procedure to categorize both positive and negative novel news days. In other words, a "forwarded news day" is defined as a day when only forwarded news is released, excluding any days with both forwarded and novel news. This ensures that market reaction and investor attention are attributed solely to forwarded news. The same

Table 2
Market response to forwarded (novel) news tone: Event study.

| Panel A. Forward News | | | | | | | | |
|-----------------------|-------------------------|--------|---------|--------------|-------------------------|---------|---------|--------------|
| Event Window | Positive Forwarded News | | | | Negative Forwarded News | | | |
| | CAAR (%) | t-stat | p-value | Significance | CAAR (%) | t-stat | p-value | Significance |
| [t-5, t-1] | 4.2106 | 1.8070 | 0.0845 | * | 0.9435 | 0.8750 | 0.3818 | |
| [t] | 10.3029 | 4.8849 | 0.0001 | *** | 0.9198 | 0.8445 | 0.3986 | |
| [t + 1, t + 5] | 10.8990 | 3.6187 | 0.0015 | *** | 0.2151 | 0.1862 | 0.8523 | |
| [t + 1, t + 10] | 9.0880 | 3.2240 | 0.0039 | *** | -0.5912 | -1.7268 | 0.0845 | * |
| [t + 1, t + 21] | 8.2612 | 3.0263 | 0.0062 | *** | -1.2959 | -2.4722 | 0.0136 | ** |

| Panel B. Novel News | | | | | | | | |
|---------------------|---------------------|--------|---------|--------------|---------------------|---------|---------|--------------|
| Event Window | Positive Novel News | | | | Negative Novel News | | | |
| | CAAR (%) | t-stat | p-value | Significance | CAAR (%) | t-stat | p-value | Significance |
| [t-5, t-1] | 3.2784 | 1.3877 | 0.1831 | | 1.5613 | 0.4072 | 0.6889 | |
| [t] | 3.2696 | 1.1491 | 0.2664 | | 1.1930 | 0.3195 | 0.7532 | |
| [t + 1, t + 5] | 1.7962 | 0.5837 | 0.5671 | | 2.2644 | 0.7162 | 0.4836 | |
| [t + 1, t + 10] | 1.5613 | 0.4072 | 0.6889 | | -1.8140 | -0.5698 | 0.5763 | |
| [t + 1, t + 21] | 1.1930 | 0.3195 | 0.7532 | | -0.7426 | -0.3065 | 0.7630 | |

This table presents the results of an event study examining the cumulative abnormal return (CAR) of all news sentiment, including positive and negative news, for forwarded news and novel news. The average cumulative abnormal return (CAAR) is calculated over several event windows. The abnormal return (AR) is computed using the CAPM as a benchmark. All returns are expressed in percentage terms. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

principle applies to “novel news day.”

We account for the possibility that some information may have been known to the public before the news was released or circulated by including the five previous trading days due to information leakage and insider trading. To address the potential for a staggered response, we include the following 21 trading days. Therefore, we establish a baseline event window of [t-5, t+21]. The average CARs are documented for the subsequent 5, 10, and 21 days after the event, as well as for the period before the event [t-5, t-1].

Table 2 presents the market responses to forwarded and novel news. The average abnormal return for positive forwarded news is 10.30%, which is statistically significant at the 1% level and economically meaningful. The abnormal return in response to negative forwarded news is approximately -1.30%, which is significant at the 5% level. However, the stock price reaction to negative forwarded news appears sluggish and with a small magnitude, persisting up to day 21. The delayed reaction to negative news is consistent with the literature (see e.g., Frank & Sanati, 2018; Gao et al., 2024), which could be attributed to the disposition effect, a behavioral bias where investors tend to hold onto losing stocks for longer periods than winning stocks. In other words, investors may be reluctant to sell their shares in response to negative news due to the fear of incurring a loss. This behavior can also be explained by loss aversion, which is a cognitive bias where people tend to feel the pain of a loss more acutely than the pleasure of a gain. As a result, investors may be more inclined to hold onto their losing stocks in the hope of a rebound, even if the rational decision would be to sell and minimize their losses. This could be due to the short-sale constraints in the Chinese stock market that hinder the immediate reflection of negative news in stock prices (Ma et al., 2021; Miller, 1977). In contrast, positive forwarded news triggers a significant and immediate increase in stock prices. The strong and rapid market reaction could be driven by investors’ motivation to capitalize on potential gains and over-confidence bias. Additionally, the herding effect, where investors follow the actions of others, may contribute to a stronger reaction to positive news (Abdellaoui et al., 2007; Barber & Odean, 2001; Bikhchandani et al., 1992; Genesove & Mayer, 2001; Odean, 1998).

In contrast, the CAR for novel news during the release window is not statistically significant, suggesting that the market may not have incorporated the information from novel news into stock prices during the news release period. It is also possible that the novel news lacks

significant information content.

4.2. Multivariate regression analysis and robustness checks

Next, following previous studies (see, e.g., You et al., 2018), we employ multivariate regression analysis to investigate the market’s response to forwarded (or novel) news shocks by controlling confounding factors that could affect both media coverage and market reactions. Specifically, we regress the tone of forwarded (or novel) news on the CAR over the [0,5] window around the news release.² The event day is defined as the day on which the forwarded (or novel) news is disseminated.

$$CAR(0,5)_{it} = a_0 + a_1 Fn_Tone_{it} + a_2 Nn_Tone_{it} + a_3 Controls_{it} + \mu_{it} \quad (1)$$

The first main variable of interest is *Fn_Tone*, which represents the tone of forwarded news released for firm *i* on news day *t*. The second main variable of interest is *Nn_Tone*, which represents the tone of novel news released for the company *i* on news day *t*. *Size* (the natural log of the firm’s market capitalization at the end of the previous fiscal year), *MB* (the ratio of the market value of equity to the book value of equity at the end of the previous fiscal year), *Lev* (the ratio of long-term total debt to the long-term total asset at the end of the previous fiscal year), *ROA* (the net income before extraordinary items scaled by the total asset at the end of the previous fiscal year), *Big4* (an indicator that takes the value of one if the firm has been audited by one of the international accounting firms, and 0 otherwise), and *log ATV* (natural logarithm of abnormal trading volume during news release window over [0,5] days).

Table 3 Column (1) is the baseline model, which that the coefficient of *Fn_Tone* is statistically significant at 1% level ($\beta = 0.2437$). One standard deviation increases in *Fn_Tone* leads to a 7.31% increase in CAR (0.2437*0.301), which is also economically significant. This finding indicates that the stock market reacts to the tone of forwarded news, even after accounting for other factors that could influence stock returns. Conversely, the coefficient of *Nn_Tone* is not significant,

² As a robustness check, to account for information leakage and investor anticipation, we employ alternative cumulative abnormal returns (CAR) measures CAR [-3,5] and CAR [-5,5]. The untabulated results remain substantively unchanged.

Table 3
Market response to forwarded (novel) news tone: OLS regression, Two-Stage-Least Squares, and Propensity score matching.

| Dependent Variable | CAR [0, 5] | F _n tone | CAR [0, 5] | CAR [0, 5] |
|---|------------------------------|-------------------------|-------------------------------|------------------------------|
| | (1) | (2) | (3) | (4) |
| <i>F_n tone</i> | 0.2427*** (6.9530) | | 0.0157*** (3.0078) | 0.1124*** (3.2871) |
| <i>Ind F_n tone</i> | | 0.4366*** (13.1190) | | |
| <i>N_n tone</i> | -0.0114 (-0.1176) | | -0.0108** (-2.3113) | 0.0313 (0.5744) |
| <i>Size</i> | -0.0068 (-0.5125) | 0.0223*** (7.9415) | -0.0002* (-1.9436) | 0.0055 (0.4504) |
| <i>MB</i> | 0.2736*** (18.0105) | -0.0057*** (-4.0003) | 0.0027*** (16.9321) | 0.3054*** (17.879) |
| <i>Lev</i> | 1.1314*** (5.0703) | -0.0117 (-0.7208) | 0.0114*** (6.3190) | 0.9465*** (12.1543) |
| <i>ROA</i> | 2.7161*** (8.2082) | 1.1920*** (30.6195) | 0.0202*** (8.7091) | 1.5291*** (5.3415) |
| <i>Big4</i> | -0.0063 (-0.1892) | -0.0505*** (-4.5596) | 0.0001 (0.1788) | 0.0217 (0.4969) |
| <i>log_ATV</i> | 0.0152 (0.7502) | -0.0043 (-0.8706) | 0.0001 (0.6075) | 0.0541*** (2.9476) |
| <i>cons</i> | -0.7004*** (-2.5878) | -0.4528*** (-7.4553) | -0.0054** (-2.3819) | -1.1833*** (-4.2323) |
| Ind FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| N | 25,681 | 25,669 | 25,669 | 14,623 |
| P-value for test | | | | |
| [F _n tone = N _n tone] | 0.0000 | | 0.0073 | 0.0002 |
| adj. R ² | 0.150 | 0.142 | 0.133 | 0.406 |
| Kleibergen-Paap F-statistics | | 431.613 | | |

This table reports the OLS regression, two-stage least square using *Ind F_n tone* as the instrument, and Propensity score matching results. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

suggesting that the market may not assimilate information from novel news events as effectively as it does for forwarded news.³

It is essential to acknowledge the potential presence of omitted variables and the possibility of reversed causality, where market reactions influence the tone of forwarded news. To address the concerns of endogeneity and measurement errors, we employ the instrumental variables method (IV) and the propensity score matching (PSM) approach.⁴ We first use two-stage regressions with an instrumental variable to account directly for the endogeneity of firms' media coverage. We utilize *Ind F_n tone* (forwarded news tone at the industry

³ In addition, we employ the VIF test and examine the correlation coefficient between the two types of news. Both analyses suggest no potential multicollinearity problem (i.e., VIF <3, 1/VIF >0.2, and correlation coefficient < 0.5, significant at 1 % level for both Pearson and Spearman correlation coefficients). As a robustness check, we regress each type of news individually, and the results remain consistent.

⁴ Building upon the prior research by You et al. (2018), which investigates the causal relationship between news and returns in the Chinese context, we incorporate additional control variables: *SOE* (a dummy variable that equals one if the firm is under state control, 0 otherwise), *STD* (the standard deviation of daily stock return over the year), *Top* (the sum of proportion of shares held by the top five shareholders at the end of the previous year), *Return* (the industry-adjusted annual stock return)—into our baseline regression. The additional controls also pass the multicollinearity test. The untabulated results further corroborate our baseline findings. Furthermore, we employ the Impact Threshold of a Confounding Variable (ITCV) test, and Oster identified sets to check the potential impact of omitted variables (Frank, 2000; Oster, 2019). The results show that our baseline regression model is free from concerns about omitted variables.

level to which the firm belongs) as the instrumental variable. *Ind F_n tone* correlates with the forwarded news tone of the focal firms (Huang & Zhang, 2022), but is not related to the individual firms' stock performance. The instrumental variable passes the under-identification test and over-identification test. Table 3 Column (2) shows that the coefficient for *Ind F_n tone* is significantly positive. The second stage result in column (3) is similar to that in column (1), alleviating the concern that our results are driven by potential reversed causality or omitted variable bias.

Second, to address potential selection bias concerns related to the association between forwarded news and market reaction analysis, we utilize the PSM. The PSM method involves matching treated and control groups based on their propensity scores, which estimate the probability of receiving the treatment (forwarded news coverage) given a set of observed covariates based on a set of firm characteristics. We start by estimating the propensity scores using a logistic regression model where the dependent variable is an indicator which equals to one if a firm receives forwarded news coverage, and zero otherwise. The independent variables considered for the matching process encompass a range of firm-level characteristics. To implement the matching process, we perform one-to-one nearest neighbor matching with a caliper of 0.01, utilizing all independent variables and ensuring common support between the treatment and control groups. After completing the matching process, there are no significant differences in observable characteristics between the treatment and control groups. The standardized bias for each variable falls below the 0.05 threshold, suggesting that the matching process has created comparable groups. The matching procedure ultimately yields a sample of 14,623 firm-year observations for further analysis of market reaction. Column (4) reports the regression result of the PSM sample. It shows that forwarded news has a statistically significant impact on market reaction. In addition, the coefficients of all control variables remain consistent in both direction and magnitude when compared to the initial pool sample analysis. In contrast, the coefficient for novel news is not significant for both the full sample and PSM sample, which is consistent with the results of the event study.

This finding raises the question of why the market reacts differently to forwarded news compared to novel news. There are several possible explanations. First, novel news introduces unexpected and often complex information to the market that investors may not have anticipated. Because investors have limited attention, time and resources to analyze new information, they may struggle to quickly understand and react to novel news. In contrast, forwarded news has already been shared and discussed among investors, meaning that its implications are likely better understood, making it easier for investors to incorporate into their decision-making processes. Second, financial markets are constantly inundated with information, leading to potential information overload. Investors may prioritize forwarded news because it has already been filtered by other news platforms as having more relevance or importance, making it easier to trust and act upon. Novel news, on the other hand, adds to the overload with new, unprocessed information that requires more time and effort to analyze, making it harder for investors to react promptly. Last, market participants often exhibit herding behavior, following the actions of others when processing and acting on the news. When news is forwarded, it is likely that other investors have already reacted, creating a bandwagon effect. In contrast, novel news lacks an established market consensus, causing investors to be more hesitant and cautious in their reactions, resulting in less effective assimilation.

Overall, our baseline results show that forwarded news generates significant market reaction, while novel news shows no significant impact on stock prices.

5. Underlying mechanisms

In Section 2, we propose three potential mechanisms through which forwarded news may evoke a more pronounced market response. First, the act of forwarding serves as a selective filter that highlights the news

with greater information content. Second, forwarding can be perceived as an act of endorsement or validation of the news content, thereby bolstering investor confidence in the news content, and influencing their investment decisions. Third, we posit that forwarding amplifies the visibility of news, capturing the limited attention of investors who are otherwise overloaded with an array of novel information.

In this section, we investigate these mechanisms in detail. Specifically, we examine the information content of forwarded news in Sections 5.1 and 5.2. Following this, in Section 5.3, we examine the trust and verification channel using the 21st Century Business Herald scandal as an exogenous shock on investors' trust. Last, Section 5.4 focuses on the attention channel by looking into investors' search and trading behaviors.

5.1. Filtering effect: Long-short portfolio analysis

Our study so far indicates that the Chinese financial market may not be effectively assimilating information from novel news, whereas forwarded news significantly impacts stock performance. However, a critical question remains: does the forwarded news contain fundamental information that can affect a firm's stock performance?

If this is indeed the case, we would expect a long-short portfolio based on forwarded news tone to generate positive alpha, indicating that the strategy can outperform the market. A long-short portfolio is constructed by taking long positions in stocks with positive news tones (i.e., buying stocks expected to perform well) and short positions in stocks with negative news tones (i.e., selling or shorting stocks expected to perform poorly). By doing this, we capture the potential value generated by differences in stock performance based on news tone.

To construct the long-short portfolios, we begin by partitioning stock-month observations into ten equal quintiles each month, based on their forwarded news tone. Stocks with the most positive forwarded news tone were placed in the top quintile, while those with the most negative tone were placed in the bottom quintile. We then calculate equal-weighted returns for the subsequent one to three months by creating a portfolio that goes long on stocks in the top quintile and short on stocks in the bottom quintile. The portfolio is rebalanced monthly and held for varying holding periods to assess the persistence of the news tone effect on stock returns.

If forwarded news contains valuable information about a firm's fundamentals, it suggests that the market has not yet fully assimilated the information contained in novel news, leading to stock price adjustments in response to forwarded news. Consequently, a long-short portfolio based on the tone of forwarded news could generate a positive alpha, outperforming the market. For comparison, we follow the same process to evaluate the performance of a long-short portfolio based on novel news.

To account for potential confounding factors, we employ the Fama French three-factor model, which regresses the long-short portfolio's time-series returns on three widely recognized risk factors, including the market risk factor (*Mkt rf*), size factor (*SMB*), and growth factor (*HML*) (Fama & French, 1993). This ensures that the observed return patterns are not driven by known risk factors in the market. The equation for the long-short portfolio return model is as follows:

$$P_{i,t} = \alpha_i + \beta_1 Mkt_rf_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \quad (2)$$

The results presented in Table 4 Panel A are consistent with the study by Huang and Zhang (2022), which examines long-short portfolios constructed based on media tone in the Chinese stock market. The positive returns for the long-short portfolio with forwarded news can persist for up to 3 months which supports the *Informative Forwarded News Hypothesis*. In contrast to prior studies, such as Tetlock et al. (2008), which find that aggregated news tone contains firm fundamental information, we show that forwarded news also possesses significant information content. However, the long-short portfolio based on the novel news tone does not generate significant abnormal returns,

Table 4
Market response to forwarded (novel) news tone: Long-short portfolio.

| Panel A: Forwarded News | | | |
|--------------------------------------|---------------------------|-----------------------------|------------------------------|
| Dependent variable: Portfolio return | | | |
| | (1) Holding 1 month | (2) Holding 2 months | (3) Holding 3 months |
| <i>alpha</i> | 0.0033 (1.1859) | 0.0100** (2.5904) | 0.0143*** (2.8573) |
| <i>MKT-Rf</i> | 1.0021 (1.1246) | 2.1935* (1.7883) | 1.8488 (1.1608) |
| <i>SMB</i> | -6.5775*** (-3.6412) | -8.3774*** (-3.3692) | -7.1359** (-2.2102) |
| <i>HML</i> | -8.1615*** (-3.2599) | -6.6385* (-1.9264) | -2.9243 (-0.6535) |
| N | 122 | 122 | 122 |
| adj. R ² | 0.091 | 0.085 | 0.040 |

| Panel B: Novel News | | | |
|--------------------------------------|---------------------------|-------------------------|---------------------------|
| Dependent variable: Portfolio return | | | |
| | (1) Holding 1 month | (2) Holding 2 months | (3) Holding 3 months |
| <i>alpha</i> | 0.0008 (0.5253) | -0.0003 (-0.1564) | 0.0002 (0.0485) |
| <i>MKT-Rf</i> | 0.3808 (0.8109) | 0.5199 (0.7429) | 0.2283 (0.2314) |
| <i>SMB</i> | -3.5148*** (-3.6929) | -4.1858*** (-2.9508) | -4.1433** (-2.0719) |
| <i>HML</i> | -3.7247*** (-2.8237) | -2.8658 (-1.4577) | -3.3551 (-1.2106) |
| N | 122 | 122 | 122 |
| adj. R ² | 0.083 | 0.058 | 0.014 |

In Panel A, we portion the stock-month observations into ten equal quintiles each month based on forwarded news tone. We first calculate the equal-weighted returns for the next 1–3 months by creating a portfolio that goes long on stocks with the most positive forwarded news tone and short on stocks with the most negative forwarded news tone. The portfolio is rebalanced every month. Following this, the long-short portfolio's time-series returns are regressed on a widely accepted risk factor. In Panel B, we portion the stock-month observations into ten equal quintiles each month based on novel news tone. We first calculate the equal-weighted returns for the next 1–3 months by creating a portfolio that goes long on stocks with the most positive novel news tone and short on stocks with the most negative novel news tone. The portfolio is rebalanced every month. Following this, the long-short portfolio's time-series returns are regressed on a widely accepted risk factor. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

consistent with our findings in the previous sections.

The results indicate that novel news does not significantly impact stock returns over short or long windows, suggesting that the market does not find all novel news informative. In contrast, the significant market reaction to forwarded news, both over short and long windows, implies that investors perceive such news as more relevant. This provides evidence of the filtering effects of forwarded news.

5.2. Whether information content alone explains the story?

In Section 5.1, we find that trading strategies based on forwarded news yield significantly positive abnormal returns, indicating that forwarded news tone does contain information content, thereby supporting our hypothesis. An underlying implication is that forwarded news is more important in nature, therefore, our finding that forwarded news generates a greater market reaction is due to the fact that forwarded novel news holds greater importance compared to other new

information. The act of forwarding is simply a proxy for the information content of the original news and does not provide incremental influence on market reaction.

To further investigate this, we repeat the event study in Table 2 by including only firm-specific forwarded news that is published when there are no other news events related to the firm within the [t-5, t+5] event window, ensuring that the forwarded news is the sole information source during this period. This approach aims to isolate the effect of forwarded news from potential confounding influences of concurrent novel news. If the market reaction is attributable solely to the information content of the original news being forwarded, we will not observe market reaction for forwarded news. However, the results in Table 5 are similar to those in Table 2. Forwarded news independently elicits a market reaction, indicating that its impact is not merely a reflection of the original news content's value.

5.3. Verification effect: 21st Century Business Herald scandal

The 21st Century Business Herald scandal highlights the potential for media outlets to mislead financial markets and shape investor perceptions.⁵ With ongoing skepticism and criticism towards market-oriented media, the impact of forwarded news on CAR after the 2014 scandal could be greater.

The 21st Century Business Herald is a prominent Chinese business newspaper known for its in-depth coverage of financial markets, economic trends, and corporate news. In 2014, its executives were arrested for extorting companies by threatening to publish negative reports, exposing corruption and severely damaging the publication's credibility. The scandal likely intensified doubts about the credibility of novel news. This led investors to place greater emphasis on forwarded news, which they perceived as more credible due to its distribution and potential verification by others. As a result, forwarded news may have a heightened impact on cumulative abnormal returns (CAR). Persistent skepticism and criticism of market-oriented media could also lead investors to exhibit confirmation bias, wherein they focus on forwarded news that aligns with their pre-existing beliefs and under-react to novel news that contradicts those views. This behavior might contribute to a more pronounced positive impact of forwarded news on CAR. Additionally, limited credible novel news sources prompted investors to engage in herding behavior, relying more on forwarded news. This collective reliance magnified the influence of forwarded news on stock prices and CAR. Finally, the scandal underscored the importance of reputable news sources for investors. Consequently, forwarded news may carry greater weight as investors aim to avoid potentially deceptive information. This shift further strengthens the impact of forwarded news on stock performance.

Given that, we expect that the 21st Century Business Herald scandal that occurred in 2014 led investors to place a greater emphasis on the content of forwarded news, amplifying its influence on stock performance. To examine our hypothesis, we regress CAR on the interaction between $F_n\ Tone$ ($N_n\ Tone$) with the year dummy $Post_scandal$ (a dummy variable which takes the value of 1 for media coverage after the 21st Century Business Herald scandal, i.e. after September 2014). The regression model is as follows:

$$CAR(0, 5)_{i,t} = a_0 + a_1 F_n\ Tone_{i,t} + a_2 N_n\ Tone_{i,t} + a_3 F_n\ Tone_{i,t} * Post_scandal + a_4 N_n\ Tone_{i,t} * Post_scandal + a_5 Controls_{i,t} + \mu_{i,t} \quad (3)$$

Table 6 displays the results. The interaction coefficient between $F_n\ Tone$ and $Post_scandal$ is positively significant, supporting the

⁵ As the largest Chinese market-oriented business newspaper, the publication faced allegations of blackmailing listed firms by threatening negative coverage. The scandal's resolution involved closing the newspaper's website and imprisoning its executives for up to 11 years.

heightened verification effects of as investors place greater importance on forwarded news after the scandal. In contrast, as anticipated, the coefficient between $N_n\ Tone$ and $Post_scandal$ is not significant.

5.4. Amplification effect: investor's attention around news shock

In this section, we investigate whether there exist variations in investors' attention in reaction to shocks from forwarded and novel news.

5.4.1. Event study: Abnormal Baidu searching volume

To evaluate investors' engagement with news, we further measure investors' attention to both types of news. In a similar vein to previous studies which use the Google search index as an indicator of investor attention (Frank & Sanati, 2018; Huang et al., 2019), we utilize the Baidu search index, China's leading search engine, to explore how investors' attention fluctuates in response to forwarded and novel news. We use the abnormal Baidu search index as a proxy to assess investors' attention levels, which are calculated using the method thoroughly described in section 3.5.

Table 7 presents the Baidu search index analysis results based on stock tickers. The findings suggest that investors respond to forwarded news shocks by actively searching through the Baidu search engine, indicating that they allocate excessive attention to stocks featured in forwarded news.

However, for novel news shocks, the results show that investors do not search excessively for stocks featured in positive novel news, suggesting that the news type significantly affects investors' attention. The negative sign of abnormal searching volume may be attributed to the presence of other events during the estimation windows, such as earnings announcements or mergers and acquisitions, which could lead to excessive searching behavior on those days. In contrast, the results show a significantly positive sign of Baidu search volume for stocks featured in negative novel news, suggesting that investors may search for the underlying stock associated with negative novel news but do not necessarily engage in trading behaviors, as indicated by the previous market reaction result.

It is crucial to highlight that investors' attention seems to be more pronounced in response to negative news compared to positive news, in line with the findings of Kim et al. (2019). This observation is evidenced by the higher magnitude of abnormal searching volumes for both negative forwarded and novel news. This phenomenon could be attributed to a natural inclination to focus on potentially detrimental information, as it may have more immediate and significant consequences for investors' portfolios. By closely monitoring negative news, investors seek to minimize losses and make more informed decisions in uncertain situations.

Taken together, investors' attention and searching behaviors may diverge based on the type (forwarded vs. novel) and tone (positive vs. negative) of the news shocks.

5.4.2. Multivariate regression analysis and robustness checks

To examine investors' heterogeneous searching behaviors in response to forwarded and novel news shocks, we follow the practice of previous research (e.g., Ding et al., 2020; Ding et al., 2022; Frank & Sanati, 2018; Kim et al., 2019) and conduct a multivariate regression analysis. Specifically, we regress the level of investor attention on the frequencies of both forwarded and novel news, while accounting for other potential factors that may impact the relationship between news and investor attention.

$$\log_SVI_{i,t} = a_0 + a_1 \ln_Fn_{i,t} + a_2 \ln_Nn_{i,t} + a_3 Controls_{i,t} + \mu_{i,t} \quad (4)$$

The dependent variable, \log_SVI , represents the natural logarithm of the abnormal Baidu search volume during news release windows over [0,5] days. \ln_Fn is the natural logarithm of one plus the number of forwarded news articles released for firm i on news day t , while \ln_Nn is

Table 5
Market response to forwarded (novel) news tone: Non- overlapping window.

| Panel A. Forward News | | | | | | | | |
|-----------------------|-------------------------|--------|---------|--------------|-------------------------|---------|---------|--------------|
| Event Window | Positive Forwarded News | | | | Negative Forwarded News | | | |
| | CAAR (%) | t-stat | p-value | Significance | CAAR (%) | t-stat | p-value | Significance |
| [t-5, t-1] | 1.1321 | 3.9202 | 0.0001 | *** | 0.0171 | 0.8274 | 0.4080 | |
| [t] | 5.0733 | 3.5504 | 0.0004 | *** | -0.0140 | -0.3414 | 0.7328 | |
| [t + 1, t + 5] | 6.0219 | 3.5445 | 0.0004 | *** | 0.0031 | 0.5494 | 0.5827 | |
| [t + 1, t + 10] | 3.0903 | 6.5985 | 0.0000 | *** | -1.0322 | -2.6892 | 0.0072 | *** |
| [t + 1, t + 21] | 2.1191 | 9.1182 | 0.0000 | *** | -1.0125 | -2.4657 | 0.0119 | ** |

| Panel B. Novel News | | | | | | | | |
|---------------------|---------------------|--------|---------|--------------|---------------------|---------|---------|--------------|
| Event Window | Positive Novel News | | | | Negative Novel News | | | |
| | CAAR (%) | t-stat | p-value | Significance | CAAR (%) | t-stat | p-value | Significance |
| [t-5, t-1] | 0.0955 | 1.1231 | 0.1787 | | 0.0511 | 0.8271 | 0.4010 | |
| [t] | 0.1251 | 0.3805 | 0.6831 | | 0.0511 | 0.5402 | 0.5621 | |
| [t + 1, t + 5] | 0.1182 | 0.8339 | 0.3813 | | 0.0522 | 0.9552 | 0.3279 | |
| [t + 1, t + 10] | 0.1539 | 1.1138 | 0.1821 | | -0.7196 | -1.8281 | 0.0691 | * |
| [t + 1, t + 21] | 0.1781 | 1.3674 | 0.1632 | | -0.0531 | -0.5392 | 0.5826 | |

This table documents the cumulative abnormal return (CAR) of all news sentiment, including positive and negative news, as determined by the event study of forwarded news and novel news in Table 2. The abnormal return (AR) is computed using the CAPM as a benchmark. All returns are expressed in percentage terms. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 6
Market response to forwarded (novel) news tone: 21st Century Business Herald scandal.

| Dependent Variable: CAR [0,5] | (1) | (2) |
|--|-------------------------------------|------------------------------------|
| <i>Fn_tone</i> | 0.1496*** (2.7038) | 0.1304** (2.1579) |
| <i>Nn_tone</i> | 0.1744** (2.2030) | 0.1028 (1.2735) |
| <i>Fn_tone * Post_scandal</i> | 0.2106*** (2.8154) | 0.1815** (2.3814) |
| <i>Nn_tone * Post_scandal</i> | -0.1288 (-0.7906) | -0.1831 (-1.1068) |
| <i>Size</i> | 0.0847*** (5.5918) | -0.0068 (-0.5110) |
| <i>MB</i> | 0.2808*** (20.9552) | 0.2734*** (17.9856) |
| <i>Lev</i> | | 1.1287*** (5.0445) |
| <i>ROA</i> | | 2.7125*** (8.0850) |
| <i>Big4</i> | | -0.0069 (-0.2077) |
| <i>log_ATV</i> | | 0.0162 (0.7946) |
| <i>cons</i> | -2.1571*** (-6.5236) | -0.6983** (-2.5630) |
| Ind FE | Y | Y |
| Year FE | Y | Y |
| N | 25,681 | 25,681 |
| P-value for test [<i>Fn_tone</i> = <i>Nn_tone</i>] | 0.0000 | 0.0000 |
| adj. R-squared | 0.143 | 0.150 |

This table reports the Impact of the 21st Century Business Herald scandal. Post scandal is a dummy variable which takes the value of 1 for media coverage after the 21st Century Business Herald scandal, i.e. after 2014. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

the natural logarithm of one plus the number of novel news articles released for company *i* on news day *t*. Control variables in the analysis include *Size*, *MB*, *Lev*, *ROA*, and *Big4*, which account for various firm-specific factors that may influence investor attention and searching behavior.

Table 8 presents compelling evidence that the coefficient of *ln_Fn* is both economically and statistically significant across all columns. This

finding implies that investors conduct more searches in response to forwarded news after the news release day, even after controlling for other factors that may affect their attention. Conversely, the coefficient of *ln_Nn* is not significantly positive at the standard level, indicating that investors do not pay attention to novel news events to the same degree as they do to forwarded news. To rule out the potential reverse causality concern, we instrument *ln_Fn* by both *ln_Ind_Fn* (the natural logarithm of one plus the total annual industry forwarded news to which the firm belongs) and *ln_Ind_AdFee* (the natural logarithm of one plus the total annual industry advertising expenditure). Firm *i* is excluded when calculating the industry average news to address the instrumental variables' endogeneity concerns. We expect that both instrumental variables have a positive correlation with the number of forwarded news at the firm level since firms operating in industries that are frequently covered by the media are more likely to be reported on, and higher advertising expenditure increases the likelihood of the presence of news. However, neither instrument is expected to have any correlation with investor attention at the firm level, satisfying the relevance and exclusion conditions. Columns (2) and (3) report the two-stage regression results. Regarding the first stage results in column (2), both *ln_Ind_Fn* and *ln_Ind_AdFee* are positively related to *ln_Fn* at the 1 % level. In the second-stage regression result in column (3), the coefficient on *ln_Fn* is positive and statistically significant which is similar to the baseline model.

To further address selection bias, we apply Propensity Score Matching (PSM), similar to the practice in Section 4.2.⁶ After completing the matching process, there are no significant differences in observable characteristics between the treatment and control groups, with standardized biases for each variable falling below the 0.05 threshold. This confirms the effectiveness of the matching procedure in creating comparable groups. As shown in column (4), this procedure yields a sample of 2392 firm-year observations for further analysis of investor attention. The results indicate that forwarded news significantly impacts investor

⁶ Specifically, we classify the dependent variable as one for firms that receive coverage through forwarded news and zero for those that do not. The independent variables for the matching process include various firm-level characteristics. We perform a one-to-one nearest neighbor matching procedure with a caliper constraint of 0.01 to improve the quality of matches, utilizing all independent variables and ensuring common support between the treatment and control groups.

Table 7
Investor attention to forwarded (novel) news tone: Event study.

| Panel A. Forward News | | | | | | | | | |
|-----------------------|-------------------------|---------|---------|--------------|-------------------------|--------|---------|--------------|--|
| Event Window | Positive Forwarded News | | | | Negative Forwarded News | | | | |
| | log_SVI | t-stat | p-value | Significance | log_SVI | t-stat | p-value | Significance | |
| [t-5, t-1] | 0.0265 | 1.7076 | 0.0880 | * | 0.3165 | 3.6339 | 0.0008 | *** | |
| [t] | 0.4994 | 28.1757 | 0.0000 | *** | 1.035 | 8.3934 | 0.0000 | *** | |
| [t + 1, t + 5] | 0.0167 | 0.9708 | 0.3319 | | 0.5809 | 4.6965 | 0.0000 | *** | |
| [t + 1, t + 10] | 0.0338 | 2.0073 | 0.0450 | ** | 0.5397 | 4.4184 | 0.0001 | *** | |
| [t + 1, t + 21] | 0.0062 | 0.3872 | 0.6987 | | 0.4688 | 4.0418 | 0.0002 | *** | |

| Panel B. Novel News | | | | | | | | | |
|---------------------|---------------------|---------|---------|--------------|---------------------|--------|---------|--------------|--|
| Event Window | Positive Novel News | | | | Negative Novel News | | | | |
| | log_SVI | t-stat | p-value | Significance | log_SVI | t-stat | p-value | Significance | |
| [t-5, t-1] | -0.0018 | -0.1360 | 0.8919 | | 0.398 | 2.6102 | 0.0183 | ** | |
| [t] | 0.4120 | 26.4011 | 0.0000 | *** | 0.9948 | 5.5078 | 0.0000 | *** | |
| [t + 1, t + 5] | -0.0613 | -4.0269 | 0.0001 | *** | 0.4668 | 2.8497 | 0.0111 | ** | |
| [t + 1, t + 10] | -0.0353 | -2.4622 | 0.0140 | ** | 0.4252 | 2.6182 | 0.0180 | ** | |
| [t + 1, t + 21] | -0.0500 | -3.7704 | 0.0002 | *** | 0.325 | 1.8505 | 0.0817 | * | |

This table documents investors' abnormal Baidu searching volume (SVI) in response to news shock, as determined by the event study of forwarded news and novel news. The average of abnormal Baidu searching volume (\log_{SVI}) is calculated from t to $t-n_1$ or t to $t+n_2$, $n_1 = 5$, $n_2 = 5, 10, 21$. \log_{SVI} is the log difference between realized and normal searching volume on each day. Normal searching volume is the median value of searching volume in the previous two months. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 8
Investor attention to forwarded (novel) news: OLS regression, Two-Stage-Least Squares, and Propensity score matching.

| Dependent Variable | log_SVI | ln_Fn | log_SVI | log_SVI |
|------------------------------|--------------------------|--------------------------|--------------------------|-------------------------|
| | (1) | (2) | (3) | (4) |
| <i>ln_Fn</i> | 0.0472** (2.4017) | | 0.4948*** (4.2509) | 0.0385* (1.7804) |
| <i>ln_Ind_Fn</i> | | 0.2890*** (11.0874) | | |
| <i>ln_Ind_AdFee</i> | | 0.2251*** (9.9889) | | |
| <i>ln_Nn</i> | 0.0132 (0.5533) | | -0.2991*** (-3.3703) | 0.0408 (1.3285) |
| <i>Size</i> | 0.2870*** (11.4052) | 0.2580*** (11.2158) | 0.1930*** (5.3978) | 0.2045*** (5.6376) |
| <i>MB</i> | -0.0059 (-0.5287) | 0.1244*** (17.7363) | -0.0382*** (-2.6031) | 0.0592*** (3.8959) |
| <i>Lev</i> | 0.0958 (0.9144) | 0.2112*** (3.0313) | -0.0516 (-0.4516) | 0.2174* (1.6653) |
| <i>ROA</i> | -5.0573*** (-13.5878) | -0.1451 (-0.9946) | -5.3510*** (-13.5752) | -1.3759*** (-2.7310) |
| <i>Big4</i> | -0.0176 (-0.2557) | 0.1562** (2.1206) | -0.0077 (-0.1002) | 0.0906 (1.2403) |
| <i>cons</i> | -1.4038*** (-2.6655) | -9.7058*** (-25.3171) | 0.0866 (0.1297) | 0.3077 (0.4243) |
| Ind FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| N | 11,492 | 30,128 | 11,492 | 2392 |
| P-value for test | | | | |
| [ln_Fn = ln_Nn] | 0.0065 | | 0.0001 | 0.0001 |
| adj. R ² | 0.162 | 0.528 | 0.087 | 0.098 |
| Kleibergen-Paap F-statistics | | 49.317 | | |

This table reports the OLS regression, two-stage least square using *ln_Ind_Fn* and *ln_Ind_AdFee* as instruments, and Propensity score matching results. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

attention, and the coefficients of all control variables remain consistent in direction and magnitude compared to the initial pooled sample analysis.

5.4.3. Moderating effect of information opacity

This section aims to examine the relationship between forwarded news and investor attention, with a focus on the moderating role of information opacity. Information opacity refers to the lack of clarity or difficulty in obtaining relevant, accurate, and timely information about a firm's financial performance, strategies, and prospects. In firms with higher information opacity, the availability of reliable data is limited, and investors with limited attention may find it challenging to assess firm value (Barberis & Xiong, 2009; Hirshleifer, 2015; Li & Yu, 2012). This scarcity of information makes investors more reliant on alternative sources, such as media news, or opinions shared on social media, to make their investment decisions. Prior studies show that the media's role as an information intermediary becomes more crucial in situations where investors need substantial amounts of idiosyncratic information about a company, especially for those operating in poor information environments (e.g., An et al., 2020; Dang et al., 2020; You et al., 2018). Consequently, investors are more likely to respond by actively conducting Internet searches to gather more information related to the news. Given that, it is worth exploring how the information environment affects investors' attention paid to forwarded news. On one hand, in environments with low-quality information, forwarded news might grab more attention because it plays a more important information intermediary role and its filtering and verification effects are more valuable to investors. On the other hand, when firm-specific information is scarce, investors are less likely to be subjected to information overload and limited attention and can digest novel news faster. This could lead to a weaker impact of forwarded news on investors' attention, as investors can process and use the novel news more efficiently.

To assess the firm-level information environment, we employ stock price synchronicity, firm opaqueness value, and the percentage of institutional ownership as indicators. These measures have been well-established in previous literature (Dang et al., 2015; Dang et al., 2020; Dechow et al., 1995; Roll, 1988). We hypothesize that the role of forwarded news in capturing investor attention is more pronounced for firms operating in information-poor environments. To test this, we interact *ln_Fn* with *Information_environment* and regress the following equation:

Table 9
Investor attention to forwarded (novel) news: Information opacity.

| Dependent Variable: log_SVI | | | |
|-----------------------------|------------------------------------|------------------------------------|-------------------------------------|
| | (1) | (2) | (3) |
| <i>ln_Fn</i> | 0.0299* (1.8485) | 0.0629*** (3.6406) | 0.0947*** (3.1587) |
| <i>Opaqueness * ln_Fn</i> | 0.3660** (2.0643) | | |
| <i>Opaqueness</i> | -1.9661*** (-2.6969) | | |
| <i>SYN * ln_Fn</i> | | 0.0310** (2.4707) | |
| <i>SYN</i> | | -0.0477 (-0.9323) | |
| <i>INST * ln_Fn</i> | | | -0.1061* (-1.7258) |
| <i>INST</i> | | | 1.2055*** (5.0766) |
| <i>Size</i> | 0.1955*** (9.1469) | 0.2762*** (11.0065) | 0.2364*** (9.729) |
| <i>MB</i> | 0.0173** (1.9749) | -0.0018 (-0.1630) | -0.0134 (-1.1920) |
| <i>Lev</i> | 0.0332 (0.3654) | 0.1233 (1.1721) | -0.0331 (-0.3133) |
| <i>ROA</i> | -1.9763*** (-6.4441) | -4.9963*** (-13.4990) | -5.3395*** (-14.1888) |
| <i>Big4</i> | 0.0796 (1.3993) | -0.0176 (-0.2529) | -0.0382 (-0.5403) |
| <i>cons</i> | 0.7855* (1.7102) | -1.1973** (-2.2616) | -0.6522 (-1.2777) |
| Ind FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| N | 10,951 | 11,492 | 11,477 |
| adj. R ² | 0.128 | 0.163 | 0.176 |

This table reports the moderating effect of the information environment on the relationship between forwarded news and investors' attention. Opaqueness is the absolute value of discretionary accrual calculated as the previous three-year moving sum of the absolute value of residual from cross-sectional regression based on modified Jone's model (Dechow et al., 1995) for each year. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 10
Alternative measure of investor attention: Event study.

| Panel A. Forward News | | | | | | | | |
|-----------------------|-------------------------|---------|---------|--------------|-------------------------|---------|---------|--------------|
| Event Window | Positive Forwarded News | | | | Negative Forwarded News | | | |
| | log_ATV | t-stat | p-value | Significance | log_ATV | t-stat | p-value | Significance |
| [t-5, t-1] | -0.0588 | -4.2194 | 0.0000 | *** | -0.0462 | -3.4622 | 0.0005 | *** |
| [t] | 0.0030 | 0.1056 | 0.9159 | | -0.0014 | -0.0545 | 0.9565 | |
| [t + 1, t + 5] | 0.0970 | 5.3804 | 0.0000 | *** | 0.0534 | 2.8149 | 0.0049 | *** |
| [t + 1, t + 10] | 0.0732 | 4.6523 | 0.0000 | *** | 0.0325 | 1.9955 | 0.0461 | ** |
| [t + 1, t + 21] | 0.0238 | 1.7004 | 0.0892 | * | -0.0114 | -0.8052 | 0.4208 | |

| Panel B. Novel News | | | | | | | | |
|---------------------|---------------------|---------|---------|--------------|---------------------|---------|---------|--------------|
| Event Window | Positive Novel News | | | | Negative Novel News | | | |
| | log_ATV | t-stat | p-value | Significance | log_ATV | t-stat | p-value | Significance |
| [t-5, t-1] | -0.0307 | -2.2989 | 0.0216 | ** | -0.0610 | -4.3243 | 0.0000 | *** |
| [t] | -0.0132 | -0.4972 | 0.6191 | | -0.1160 | -3.8837 | 0.0001 | *** |
| [t + 1, t + 5] | 0.0000 | 0.0017 | 0.9986 | | -0.0704 | -2.9069 | 0.0037 | *** |
| [t + 1, t + 10] | 0.0040 | 0.2407 | 0.8098 | | -0.0556 | -2.6679 | 0.0077 | *** |
| [t + 1, t + 21] | -0.0045 | -0.3039 | 0.7612 | | -0.0269 | -1.7189 | 0.0858 | * |

This table documents investor abnormal trading volume in response to news shock, as determined by the event study of forwarded news and novel news. The average of abnormal trading volume is calculated from t to t-n1 or t to t + n2, n1 = 5, n2 = 5, 10, 21. Abnormal trading volume (*log_ATV*) is the log-transformation of abnormal trading volume during news release window over [0,5] day. Normal trading volume is the median value of trading volume in the previous two months. t-statistics and p-statistics appear in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

$$\log_SVI_{i,t} = a_0 + a_1 \ln_Fn_{i,t} + a_2 \ln_Fn_{i,t} * Information_environment_{i,t} + a_3 Information_environment_{i,t} + a_4 Controls_{i,t} + \mu_{i,t} \quad (5)$$

where *Information environment* is a generic term alternatively standing for *Opaqueness* (the absolute value of discretionary accrual calculated as the previous three-year moving sum of the absolute value of residual from cross-sectional regression based on modified Jone's model (Dechow et al., 1995) for each year), *SYN* (log-transformation of *adj.R*² of firm-year weekly return regressing on the weekly market and weekly value-weighted industry return), and *INST* (percentage of institutional ownership).

Table 9 shows that the coefficients of the interaction terms are significant across all columns. This finding suggests that the effect of forwarded news is more pronounced for firms operating in relatively opaque information environments, those with higher stock price synchronicity, and those with a lower percentage of institutional ownership. It is possible that the filtering effect and verification effect of forwarded news become more important in these specific contexts. Overall, our results show that forwarded news plays a vital role in attracting investors' attention, particularly for firms with limited access to information.

5.4.4. Alternative measure of investor attention: Abnormal trading volume

We examine the robustness of our results using abnormal trading volume as an alternative measure of investor attention. Abnormal trading volume is a suitable proxy for investor attention, as it captures shifts in interest and engagement among market participants. The underlying rationale is that increased investor attention towards a specific stock or financial instrument leads to a higher likelihood of trading, resulting in elevated trading volumes. Abnormal trading volume, representing deviations from the average trading volume, thus serves as an indicator of changes in investor attention. By considering this measure, we can assess the stability of our findings across different proxies for investor attention.

Previous studies, such as those by Barber and Odean (2008) and Ma et al. (2021), have used abnormal trading volume as a measure of investor attention, providing empirical support for its effectiveness in capturing variations in the focus of market participants. Our analysis, which includes results from Table 10 and Table 11, aligns with the findings presented in Table 7 and Table 8. This consistency across

Table 11
Alternative measure of investor attention: OLS regression.

| Dependent Variable: log_ATV | | |
|--|-----------------------|-------------------------|
| | (1) | (2) |
| <i>ln_Fn</i> | 0.0131** (2.0407) | 0.0120* (1.9386) |
| <i>ln_Nn</i> | 0.0040 (0.4221) | 0.0036 (0.3895) |
| <i>Size</i> | 0.0290*** (4.3087) | -0.0287*** (-3.9622) |
| <i>MB</i> | 0.0081** (2.4409) | -0.0013 (-0.3844) |
| <i>Lev</i> | | 0.6055*** (12.0042) |
| <i>ROA</i> | | 1.7923*** (23.7517) |
| <i>Big4</i> | | 0.0520** (1.9901) |
| <i>cons</i> | -0.0488 (-0.3309) | 0.9196*** (6.0474) |
| Ind FE | Y | Y |
| Year FE | Y | Y |
| N | 30,128 | 30,128 |
| P-value for test [<i>ln_Fn</i> = <i>ln_Nn</i>] | 0.0114 | 0.0167 |
| adj. R ² | 0.209 | 0.256 |

This table reports investors trading behaviors in response to forwarded and novel news using OLS regression. *log_ATV* is the log-transformation of abnormal trading volume during news release window over [0,5] day. t-statistics robust to heteroscedasticity and clustered by firm are reported in parentheses. Refer to Appendix A for definitions of variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

different measures of investor attention further validates the robustness of our results.

6. Conclusions

In an efficient market, the information derived from novel news can immediately be incorporated into stock prices. However, the reliability and accuracy of media coverage have been challenged in the Chinese market for a long time. Forwarded news, which has been screened and shared by other media outlets, may differ from novel news. Using event study and multivariate regression analysis, we find that forwarded news has a more significant influence on stock prices than novel news.

We further investigate the underlying mechanisms of the distinct market reaction, and uncover three effects of forwarded news, namely, filtering effect, verification effect and amplification effect. First, we find that trading strategies based on forwarded news tones generate significantly positive abnormal returns, supporting the “*informative forwarded news hypothesis*”. The act of forwarding serves as a filter that selects news with greater information content. The findings emphasize the importance of news heterogeneity for investors when assessing firm fundamental values in financial markets. By considering the tone of forwarded news, investors can make more informed decisions and achieve greater returns.

We then explore the verification effect by examining the impact of news scandals as an exogenous shock. Our findings reveal that forwarded news triggers a stronger market response in the aftermath of news scandals, suggesting that the verification effect of forwarded news intensifies when social trust in the media is compromised. Our results also highlight the importance of verifying the credibility of news sources in the Chinese stock market to facilitate informed decision-making. Our study is among the first to investigate the trust issues of the Chinese media industry and examine the role of forwarded news.

For the amplification effect, we show that forwarded news garners investors’ attention but not novel news, particularly for firms with poor information environments. The results can be explained by investors’

limited attention. As retail investors dominate the Chinese stock market and they are more prone to limited attention, forwarded news plays a pivotal role in information distribution.

These findings have several practical implications for investors, regulators, policymakers, and media organizations. For investors, recognizing the value of forwarded news can enhance decision-making processes, as forwarded news often carries higher credibility and relevance due to its social filtering process. By focusing on this type of news, investors can make more informed decisions. Understanding the verification and amplification effects of forwarded news helps investors develop strategies to discern information quality and react appropriately.

For regulators and policymakers, measures to enhance the positive effects of forwarded news could be beneficial. Encouraging the dissemination of high-quality, credible news through stringent standards, transparency in news sourcing, and incentivizing the sharing of well-vetted information can amplify these effects. Additionally, developing stringent policies to enhance the quality of novel news can help the market incorporate information more timely.

For media organizations, particularly in China, our study underscores the importance of improving public trust in their reporting. Ensuring the accuracy and credibility of news through rigorous fact-checking and clear labeling of forwarded news can help build trust. Enhanced public trust will lead to a more informed investor base, reduce the impact of news fraud and low-quality reporting, and contribute to a more stable financial market environment.

The generalizability of our findings outside China requires careful consideration due to the unique characteristics of the Chinese stock market. The heavy reliance on media by retail investors, the slower dissemination of novel news due to regulatory influences, and the pronounced filtering and verification effects due to varying media quality and frequent financial scandals, make the Chinese market distinct. These factors mean that our results on the impact of forwarded news might not directly apply to other markets with different regulatory environments, media landscapes, and investor compositions. Specifically, the effects of forwarded news may be weaker in more mature markets with higher news quality and a greater proportion of institutional investors. However, our findings could still be relevant for stocks with a significant presence of retail investors or firms with opaque information environments in these markets. Caution should be exercised when generalizing these insights, and further research is needed to understand the roles of novel and forwarded news in different regulatory and institutional settings.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We thank Samuel Vigne (the editor), two anonymous referees, Dimitris Margaritis, Henk Berkman, John Lee, Yeguang Chi, Alejandro Bernal, as well as seminar and conference participants at University of Auckland, and the International Finance and Banking Society (IFABS) Conference (Oxford, 2023). Jiaxin Duan acknowledges financial support from Macau University of Science and Technology Faculty Research Grants (Project No. FRG-24-044-MSB).

Appendix A. Variable definitions

| Acronym | Variable | Definition |
|---------------------------|---|--|
| <i>F_{n_tone}</i> | Forwarded news tone | <i>F_{n_tone}</i> is the forwarded news tone released for a firm on news day <i>t</i> |
| <i>N_{n_tone}</i> | Novel news tone | <i>N_{n_tone}</i> is the novel news tone released for a firm on news day <i>t</i> |
| <i>Ln_Fn</i> | Forwarded news counts | <i>Ln_Fn</i> is the natural log of one plus the number of forwarded news released for a firm in the year |
| <i>ln_Nn</i> | Novel news counts | <i>ln_Nn</i> is the natural log of one plus the number of novel news released for a firm in the year |
| <i>CAR</i> | abnormal return | The average of cumulative abnormal return in response to news shock, as determined by the event study of forwarded news and novel news |
| <i>CAR[0,5]</i> | Cumulative abnormal return | <i>CAR[0,5]</i> is the cumulative abnormal returns during news release windows over [0,5] day |
| <i>log_SVI</i> | Baidu search index | <i>log_SVI</i> is the log-transformation of abnormal search volume during news release windows over [0,5] day |
| <i>log_ATV</i> | Abnormal trading volume | <i>log_ATV</i> is the log-transformation of abnormal trading volume during news release windows over [0,5] day |
| <i>Size</i> | Firm size | <i>Size</i> is defined as the natural log of firm's market capitalization at the end of the previous fiscal year |
| <i>MB</i> | Market-to-book value | <i>MB</i> is defined as the ratio of market value of equity to the book value of equity at the end of the previous fiscal year |
| <i>Lev</i> | Leverage | <i>Lev</i> is defined as the ratio of long-term total debt to the long-term total asset at the end of the previous fiscal year |
| <i>ROA</i> | Return-on-assets ratio | <i>ROA</i> is defined as the net income before extraordinary items scaled by the total asset at the end of the previous fiscal year |
| <i>Big4</i> | Audit status | The <i>Big4</i> is set to one if the firm has been audited by one of the international accounting firms, 0 otherwise |
| <i>SMB</i> | Size factor | Return of a portfolio of small stocks minus the return of a portfolio of big stocks |
| <i>HML</i> | Growth factor | Return on a portfolio of stocks with high book-to-market ratio minus the return on a portfolio of stocks with low book-to-market ratio |
| <i>Mkt_Rf</i> | Market risk factor | market return minus return on the one-year deposit rate |
| <i>Post_scandal</i> | Post 21st Century Business Herald scandal | a dummy variable which takes the value of 1 for media coverage after the 21st Century Business Herald scandal, i.e. after September 2014 |
| <i>Opaqueness</i> | Information opaqueness | <i>Opaqueness</i> is the absolute value of discretionary accrual calculated as the previous three-year moving sum of the absolute value of residual from cross-sectional regression based on modified Jone's model (Dechow et al., 1995) for each year |
| <i>SYN</i> | Stock price synchronicity | Log-transformation of adj.R ² of firm-year weekly return regressing on the weekly market and weekly value-weighted industry return |
| <i>INST</i> | Institutional ownership | percentage of institutional ownership |
| <i>ln_Ind_Fn</i> | Industry forwarded news | <i>ln_Ind_Fn</i> is the natural log of 1 plus total annual forwarded industry media coverage to which the firm belongs |
| <i>ln_Ind_AdFee</i> | Advertisement expenditure | <i>ln_Ind_AdFee</i> is the natural log of 1 plus the firms' annual advertisement expenditure |
| <i>Ind_Fn_tone</i> | Industry forwarded news tone | <i>Ind_Fn_tone</i> is forwarded news tone at the industry level to which the firm belongs |

Appendix B. Forwarded news identification

To identify forwarded news, we employ the Vector Space Model (VSM), a method previously utilized in research such as Salton and McGill (1983) and Tetlock (2011), which measures the textual similarity of news articles. We analyze similar news within a database of listed company news, using cosine distance to evaluate the similarity in information content between each news article. In this model, news texts are represented as n-dimensional vectors (e.g., *V*₁ for news 1, *V*₂ for news 2).

We first extract keywords from each news article through word segmentation, converting each article into keyword vectors. Subsequently, as illustrated in the equations below, we calculate the cosine similarity (COS similarity) by assessing the similarity between the keyword vectors of two news articles. To identify forwarded news, we employ the Vector Space Model (VSM), a method previously utilized in research such as Tetlock (2011), which measures the textual similarity of news articles.

$$V_1 = (W_1, W_1, \dots, W_n);$$

$$V_2 = (\psi_1, \psi_2, \dots, \psi_2);$$

In this context, the symbols '*w*' and '*ψ*' denote the weights assigned to the *i*-th word within the news document. The method to compute similarity is described by the following formula:

$$\text{Similarity} = \text{COS}\theta = \frac{V_1 \cdot V_2}{|V_1| \cdot |V_2|}.$$

Here, *θ* represents the angle between vectors *V*₁ and *V*₂, where (·) denotes the dot product operation, and |*V*| represents the magnitude of vector *V*. A higher similarity value signifies a greater degree of similarity between the two documents.

The resulting similarity scores range from -1 to 1, where a score closer to 1 signifies a greater similarity between two news articles. We collect articles tagged as "forwarded from..." and classify those with a similarity score exceeding 90 % as forwarded news. Considering that identical news articles can be reported by various media outlets at different times, we do not establish the similarity score threshold at 100 %.

Examples for the calculation of similarity score:

| Original news content | News content | Similarly score |
|-------------------------------------|-----------------------------|-----------------|
| Original text:安泰集团陷债务泥潭 控股股东全部股权被冻结 | Text 1:安泰集团陷债务泥潭控股股东全部股权被冻结 | 1 |
| Original text:安泰集团陷债务泥潭 控股股东全部股权被冻结 | Text 2:安泰集团控股股东所持 32%股份被冻结 | 0.407 |
| Original text:安泰集团陷债务泥潭 控股股东全部股权被冻结 | Text 3:安泰所持股份被冻结 | 0.371 |

Translation: Original news text: "Antai Group falls into debt mire, controlling shareholder's entire equity is frozen".

Text 1: "Antai Group falls into debt mire, controlling shareholder's entire equity is frozen".

Text 2: "Antai Group's controlling shareholder's 32% shareholding is frozen".

Text 3: "Antai's shareholding is frozen".

Process to Calculate the Similarity Score.

1. Create a Corpus

The corpus is formed from the texts under comparison.

Text1: “Antai Group falls into debt mire, controlling shareholder’s entire equity is frozen”.

Text2: “Antai Group’s controlling shareholder’s 32% shareholding is frozen”.

2. Identify unique words

We identify unique words across both texts, resulting in the set: [32, Antai, controlling, debt, entire, equity, falls, frozen, group, into, mire, shareholder, shareholding].

3. Calculate TF (Term Frequency) for each word in each text

TF is computed as the frequency of a word in a document relative to the total word count of that document. For example, in Text 1, the word “antai” occurs once out of ten words, giving a TF of 1/10.

4. Calculate IDF (Inverse Document Frequency) for each word in the Corpus

IDF is the logarithm of the ratio of the total number of documents to the number of documents containing the word. To prevent division by zero, 1 is added to both the numerator and denominator. For example, IDF for a word that appears in both documents (like “antai”) is $\ln(2/2) = 0$. But for practical purposes and to avoid division by zero, TF-IDF implementations add 1 to the denominator, and also typically add 1 to the numerator, so it would be $\ln((2 + 1)/(2 + 1)) = 0$.

5. Calculate TF-IDF Score

The TF-IDF score is the product of TF and IDF for each word within each document.

6. Form the Vectors

Each document is then represented as a vector with these TF-IDF scores. The resulting vectors comprise the TF-IDF scores corresponding to each unique word across the texts, with each vector element representing a unique word from the corpus.

7. Normalize the Vectors

Finally, these vectors are normalized to unit length, which is crucial for the subsequent cosine similarity calculation.

By following these steps, we can accurately represent documents as numerical vectors and quantify their similarity effectively.

Example:

TF-IDF Vectors

The TF-IDF vectors for Text1 and Text2, corresponding to the terms `['32', 'antai', 'controlling', 'debt', 'entire', 'equity', 'falls', 'frozen', 'group', 'into', 'mire', 'shareholder', 'shareholding']`, are:

- Text1: `[0.000, 0.244, 0.244, 0.342, 0.342, 0.342, 0.342, 0.244, 0.244, 0.342, 0.342, 0.244, 0.000]`
- Text2: `[0.470, 0.334, 0.334, 0.000, 0.000, 0.000, 0.000, 0.334, 0.334, 0.000, 0.000, 0.334, 0.470]`

The *Cosine* similarity score of approximately 0.407 suggests a moderate similarity between the two texts. This is due to commonalities with terms such as “Antai”, “controlling”, “frozen”, and “shareholder”, while divergences arise from words like “debt”, “mire”, “32”, and “shareholding”. The TF-IDF approach accounts for the term frequency within each text as well as their significance across the entire corpus.

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