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In the swirl of rumors: Corporate rumors and analyst forecast dispersion

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ABSTRACT

This study investigates whether and how corporate rumors affect analyst forecast dispersion. Using hand-collected rumors involving Chinese A-share listed firms from 2007 to 2023, we find that corporate rumors significantly increase analyst forecast dispersion, and this effect is robust to a battery of sensitivity tests. Mechanism tests reveal that corporate rumors aggravate analyst forecast dispersion by amplifying media disagreement and increasing information uncertainty. Moreover, the rumor effect is more significant for firms with higher operational uncertainty, greater information opacity, less analyst communication, and those located in regions with lower media ethics. Taken together, our findings suggest that the emergence of corporate rumors can disrupt the information environment of the rumored firms.

1. Introduction

The capital market is a vast ocean of information gathering, but it is also a fertile ground for rumors (Ahern & Sosyura, 2015; Schindler, 2007). Different from the formal information disclosed by listed companies or official agencies, rumors are a unique form of news characterized by great uncertainty and sensational stories (Clarkson, Joyce, & Tutticci, 2006; Jia, Redigolo, Shu, & Zhao, 2020). Despite the lack of verification, they can quickly spread and capture market attention, often resulting in significant market reactions. Previous studies have primarily focused on the impact of corporate rumors on investor trading activities and stock returns using event study methods (e.g., Clarkson et al., 2006; Davis, Khadivar, & Walker, 2021; Gao & Oler, 2012; Marshall, Visaltanachoti, & Cooper, 2014; Shi, Ye, & Zhao, 2023). However, the influence of corporate rumors on the information environment of the implicated firms remains largely unexplored. In this study, we expand the investigations on the externalities of corporate rumors in capital markets by incorporating the perspective of analyst forecast dispersion.

As crucial information intermediaries in the capital market, sell-side analysts continuously gather and process a range of financial and non-financial information and provide earnings forecasts for firms, offering valuable insights for investors' decision-making (Cheng, 2005; Gleason & Lee, 2003). Nevertheless, analyst earnings' forecasts generally exhibit disagreement or a lack of consensus. In financial research, such disagreement is used to explain heterogeneous opinions and the resulting return anomalies (e.g., Doukas, Kim, & Pantzalis, 2009; Garfinkel, 2009; Goetzmann & Massa, 2005; Johnson, 2004), while accounting scholars generally view it as proxies for imperfect information or information uncertainty (e.g., Jiang, Lee, & Yi, 2005; Wang, 2020; Zhang, 2006). For example, Avramov, Chordia, Jostova, and Philipov (2009) suggest that greater analyst forecast dispersion reflects financial distress resulting from credit rating downgrades. Ali, Liu, Xu, and Yao (2019) show that temporary withholding of bad news by firms increases forecast dispersion among analysts and thus leads to low subsequent stock returns. Wang (2020) argues that analyst forecast dispersion serves as an indication of investors' perceived uncertainty concerning earnings, ultimately influencing their trading decisions and the efficiency of stock pricing. Given these significant economic implications, examining the cross-sectional determinants of analyst forecast dispersion in the context of corporate rumors is essential for investors, analysts, managers, and scholars alike.

Previous research has generally attributed analyst forecast dispersion to the volatility of firm fundamentals and the imperfect information (Johnson, 2004; Zhang, 2006). Analyst earnings' forecast dispersion reflects the disagreements among analysts' heterogeneous beliefs about a company's future earnings. In this sense, fluctuations in firm fundamentals are closely related to operation uncertainty, leading to a wider forecast range (e.g., Chourou, Purda, & Saadi, 2021; Li & Zhang, 2025;

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Wang, 2020). On the other hand, the incompleteness of public information prompts analysts to assign different confidence weights to uncertain information, increasing the degree of forecast dispersion (e.g., Gao, Wen, & Yu, 2021; Li, Huang, Cao, & Chen, 2025; Wang, Ma, & Wang, 2024; Yin, Han, & Shen, 2024; Zhang, 2006). Nevertheless, as informal information that floods the capital market, whether and how corporate rumors affect analysts' consensus beliefs or opinion divergence remain uncovered. Hence, this study aims to fill this gap by investigating the impact of corporate rumors on the dispersion in analyst earnings' forecasts.

The public often misunderstands rumors as distorted, irrational, and false information (Sunstein, 2009). However, rumors are essentially unverified information in circulation, which may be proven true or false in the future (Cai, Quan, & Zhu, 2023; Clarkson et al., 2006; Rosnow, 1991). Regarding corporate rumors, they can be true information originating from internal leaks or market early detection, but they can also be fabricated by rumormongers. Hence, the emergence of corporate rumors can increase the exposure of the implicated firms, encouraging information collection and promoting information dissemination (Clarkson et al., 2006; Kosfeld, 2005; Zhang, Su, Weigang, & Liu, 2018). On the other hand, they can also aggravate market disagreement and media bias, and to some extent, shape investor sentiment (Ahern & Sosyura, 2015; Jia et al., 2020; Jia, Ruan, & Zhang, 2017). As such, the potential impact of corporate rumors on the information environment of the rumored firms remains a matter of debate.

Due to the duality of corporate rumors, we propose two competing hypotheses regarding their relationship with analyst forecast dispersion. From the information promotion perspective, rumors can promote information discovery, thereby mitigating analyst forecast dispersion. This is because a rumor may tell an undisclosed true story (Ahern & Sosyura, 2015; Cai et al., 2023; Zhang et al., 2018), bringing effective information increments to analyst decision-making. Even if these rumors are largely incorrect, they are expected to supplement the incompleteness of company disclosures by encouraging market information mining and dissemination (Bommel, 2003; Schindler, 2007). From the noise interference perspective, rumors may increase the dispersion of analyst earnings' forecasts by disrupting the information environment of the firms involved. As unofficial explosive news, the rumor emergence also causes media disagreement and bias (Ahern & Sosyura, 2015; Jia et al., 2017), which indirectly aggravates analyst earnings' forecasts. Meanwhile, due to the high uncertainty of rumors as incomplete information, they may directly exacerbate the information uncertainty of the rumored firms, making analysts more divergent.

We empirically examine the impact of corporate rumors on analyst forecast dispersion using a dataset of Chinese A-share listed firms from 2007 to 2023. Our baseline regressions reveal a significantly positive relationship between corporate rumors and analyst forecast dispersion. Specifically, compared to firms without rumors, analyst forecast dispersion is 24.19 % higher in the rumored firms, and one additional standard deviation in the continuous rumor measure leads to a 6.05 % increase in analyst forecast dispersion. To further strengthen the robustness of our main finding, we perform difference-in-difference (DID) estimations to address potential reverse causality, employ local education and lawyer coverage as two instrument variables to mitigate the causality caused by omitted variables, and reconstruct the sample using one-to-one nearest neighbor propensity score matching (PSM) approach to alleviate model misspecification concerns due to covariates unbalance.[1] We also use alternative measures of analyst forecast dispersion and control for multidimensional fixed effects in multiple dimensions. The regression results are consistent with our main conclusion.

To gain further insights into the impact of rumors on analyst disagreement, we conduct several additional analyses. We firstly explore the mechanisms through which rumors influence analyst forecast dispersion. Results from the two-stage mediation effect tests show that corporate rumors are positively related to media disagreement and information uncertainty, both of which also significantly increase analyst forecast dispersion. In addition, we perform some cross-sectional tests and find that the rumor effect is more pronounced for firms with greater operating uncertainty, higher information opacity, less analyst site visits, and those located in regions with low media ethics. These findings are essentially consistent with the perspectives of fundamental volatility and imperfect information underlying analyst disagreement (Johnson, 2004; Zhang, 2006), and they also offer insights into mitigating or managing the adverse effects of rumors on firm information environment.

Last, we deepen our understanding of the rumor effect by investing the impacts of various types of corporates rumors on analyst forecast dispersion. We find that corporate rumors related to firms' cash flows, including those from daily operation and capital operation, have a greater impact on analyst forecast dispersion than those telling stories about firm information disclosure and other rumors outside of these categories. In terms of rumor tones, it shows that analyst forecast dispersion is insensitive to negative rumors but shows a more significant response to neutral and positive rumors. Moreover, corporate rumors technically clarified by listed companies have a weaker impact on analyst disagreement than those without technical clarifications. Overall, these findings suggest that analysts should analysts should take seriously the potential impact of cash flow rumors and positive/neutral rumors on information environment, and that listed companies should issue technical clarifications to proactively address the adverse effect of corporate rumors.

This study contributes to existing literature in three ways. First, we expand the literature on the determinants of analyst earnings' forecast dispersion. Analysts play a critical role as information intermediaries in the capital market, and their earnings forecasts offer valuable insights for investment decisions (Chan & Hameed, 2006; Cheng, 2005; Gleason & Lee, 2003). Despite the widespread application of analyst forecast dispersion as a proxy for uncertainty risk or information uncertainty in empirical research in finance and accounting, studies on its determinants are limited. Prior literature has primarily examined some factors influencing analyst forecast dispersion, including earnings volatility (Wang, 2020), economic policy uncertainty (Chourou et al., 2021), information uncertainty (Gao et al., 2021; Zhang, 2006), and analyst strategic behaviors (Liu & Natarajan, 2012), etc. This study broadens the investigation by exploring the impact of corporate rumors on analyst forecast dispersion, which has important implications for understanding the cross-sectional differences in analyst forecast divergences.

Second, we enrich the research on the market consequences of corporate rumors. The capital market is replete with rumors, which are non-official, unverified, and highly uncertain messages (Ahern & Sosyura, 2015; Jia et al., 2017; Schindler, 2007). Theoretical studies generally regard rumors as private information that influences investment decisions (Kimmel, 2004; Zhang et al., 2018), while empirical research primarily examines the effect of corporate rumors on short-term investors' trading activities and the subsequent stock returns (e.g., Clarkson et al., 2006; Davis et al., 2021; Gao & Oler, 2012; Marshall et al., 2014; Shi et al., 2023). This study uncovers the impact of corporate rumors on the information environment through the lens of analyst forecast dispersion, supporting the noise features of rumors revealed in Cai et al. (2023). Our findings also suggest that even professional analysts can be swayed by rumors to generate significant dispersion, which augments the understanding of the consequences of corporate rumors in financial markets.

[1] We use the "*Interpretation on Several Issues Concerning the Application of Law in the Handling of Criminal Cases Involving Defamation through Information Networks*" (hereafter "*Interpretation of Online Defamation*") issued by China's Supreme People's Court (CSPC) and China's Supreme People's Procuratorate (CSPP) in 2013 as an exogenous policy that restricts corporate rumors to design the DID tests, and find that the rumor effect is weakened after 2013. Please see section 4.2.1 for more details.

Third, this study adds new evidence on the adverse effects of media hype in capital markets. Prior studies suggest that business media play a crucial role in discovering and disseminating financial information, which promotes price discovery and enhances external monitoring (e.g., Bushee, Core, Guay, & Hamm, 2010; Dang, Dang, Hoang, Nguyen, & Phan, 2020; Dyck, Volchkova, & Zingales, 2008; Engelberg & Parsons, 2011). Nevertheless, media news reporting is not always impartial and unbiased, and media organizations often hype up sensational news to attract wide attention (Ahern & Sosyura, 2015; Jia et al., 2020). In this study, we suggest that corporate rumors spread by the media directly lead to media disagreement and thus amplifies analyst forecast dispersion. Meanwhile, we also reveal the importance of media ethics in mitigating the rumor effect. These findings provide new evidence of the potential negative impacts of media hype and offer insights for investors, analysts, and managers to critically evaluate media reporting.

The rest of this paper proceeds as follows. Section 2 develops the hypothesis, Section 3 outlines our research design, Section 4 presents the main empirical findings, Section 5 provides several supplementary analyses, and Section 6 offers concluding remarks.

2. Literature review and hypothesis development

2.1. Literature review

Sell-side analysts play a crucial role as information intermediaries by collecting and processing various market information to provide earnings forecasts and stock recommendations to investors (e.g., Cheng, 2005; Gleason & Lee, 2003). Although analysts are information experts in the capital market, their collective opinions often diverge, manifested in significant discrepancies in earnings forecasts or stock ratings for specific companies. Besides intrinsic factors such as analysts' industry experience and cognitive abilities, prior research typically attributes analyst disagreement to the volatility of firm fundamentals and the imperfect information (Johnson, 2004; Zhang, 2006). According to the fundamental volatility theory, analysts' forecasts or ratings are based on the actual operating conditions of the target company; therefore, higher volatility or uncertainty in the company's fundamentals can hinder analysts' valuation predictions and exacerbate disagreements within the analyst community (e.g., Frankel & Litov, 2009; Gu & Wu, 2003; Johnson, 2004). For instance, Wang (2020) demonstrates that analysts' forecast disagreement is higher for companies with greater earnings volatility, while Chourou et al. (2021) find that economic policy uncertainty increases fundamental volatility, reducing the consistency of analysts' consensus forecasts. Li and Zhang (2025) further show that digital transformation mitigates analyst earnings forecast dispersion by reducing earnings volatility.

On the other hand, the imperfect information theory suggests that the incompleteness of firm information prompts analysts to assign different confidence weights to uncertain information, thereby increasing the degree of forecast dispersion (e.g., Atmaz & Basak, 2018; Jiang et al., 2005; Yang, Lu, & Xiang, 2020; Zhang, 2006). For example, Zhang (2006) suggests that imperfect information closely relates to valuation uncertainty, which in turn leads to greater analyst divergence. Li, Wong, and Yu (2020) hold that maintaining close contact between companies and analysts can promote the circulation of information among the analyst community and thus reduce analyst disagreement. Gao et al. (2021) find that the COVID-19 pandemic significantly reduced analysts' site visits and face-to-face interactions with target companies, leading to information blockades and subsequently increasing analyst forecast dispersion. More recently, Tang, Qin, and Qi (2025) and Li et al. (2025) indicate that the establishment of circuit courts and the reform of the registration system effectively enhance corporate disclosure transparency and reduce information asymmetry, which is conducive to a lower degree of analysts' earnings forecast disagreement.

Despite the extensive discussions in the existing literature on analyst forecast dispersion centered around firm-level characteristics such as fundamental volatility and information environment, the impact of widespread rumors in the market on the collective beliefs of analysts has yet to be explored. In this study, we focus on whether and how corporate rumors affect the dispersion of analyst' earnings forecasts. Given that corporate rumors typically emerge as breaking news, their potential impact on the consensus or disagreement of analyst forecast can be attributed to the shock in information environment.

2.2. Main hypothesis

Distinct from the official information disclosed by listed companies (such as daily disclosure and financial reports), corporate rumors are a special type of unofficial and unverified news in dissemination (Rosnow, 1991; Schindler, 2007). Despite such informality, a rumor per se is informative, which could fill the gaps of incomplete information and thus promote consensus among analysts. First, anecdotes and literatures suggest that corporate rumors may be accurate information that has been concealed by the company but leaked internally or detected early by the market. For example, the doubts or accusations against listed companies (such as German payment company Wirecard, American energy giant Enron, and Chinese composite materials company Kangde Xin, etc.) were initially deemed as false reports or even defamatory by the companies involved, but were eventually validated. Additionally, Ahern and Sosyura (2015) found that 33 % of the 501 merger rumors they collected from the US financial media were eventually realized. In the study of Cai et al. (2023), approximately 35 % of the 3979 rumors denied by Chinese listed companies were eventually proven to be correct news. Regardless of the authenticity of the rumors, they can also trigger a new round of information mining and dissemination. In particular, corporate rumors often spark intense discussions and in-depth verification by investors (Schindler, 2007; Zhang et al., 2018), and they are widely disseminated by commercial media (Jia et al., 2017; Kiymaz, 2001).

Nonetheless, the rumors are essentially a type of imperfect information, which may disrupt the information environment of the involved firms and thus increase the dispersion of analyst earnings' forecasts. Specifically, the emergence of rumors usually triggers media controversy and disagreement, which indirectly hindering analyst consensus. Previous studies show that the emergence of rumors usually cause the targeted company to become the focus of public opinion, attract media hype and controversy, and further exacerbate media disagreement (Jia et al., 2017; Kosfeld, 2005). Since media news is an important information resource for analyst decision-making (Amin, Hasan, & Malik, 2020; Hossain, Mammadov, & Vakilzadeh, 2014; Huang & Mamo, 2016), the increased media disagreement caused will weaken the availability of media news, leading to more dispersed earnings forecasts. Furthermore, rumors are inherently uncertain (Rosnow, 1991), which can directly exacerbate information uncertainty around the accused firms and increase the dispersion in analyst forecasts. As suggested by Cai et al. (2023), corporate rumors function as a form of noise interference, amplifying information uncertainty and fueling market sentiment, while providing minimal incremental information. Given that information uncertainty is a key reason for the lack of consensus in analyst predictions (Zhang, 2006), the emergence of rumors may result in greater analyst disagreement.

Drawing on the imperfect information theory, corporate rumors may have two opposing effects on firm information environment. On one hand, they can repair incomplete information by revealing the truth and stimulating information mining and dissemination. On the other hand, they can disrupt the information environment by exacerbating media bias and disagreement or increasing information uncertainty. The former suggests that corporate rumors converge analyst consensus, while the latter implies that rumors exacerbate the disagreement among analysts. Hence, we propose the following competitive hypotheses:

Hypothesis H1a. *Corporate rumors reduce the dispersion in analyst* *forecasts of the rumored firms.*

Hypothesis H1b. *Corporate rumors increase the dispersion in analyst forecasts of the rumored firms.*

3. Research design

3.1. Sample and data

The initial sample comes from all firms listed in the Chinese A-share market during 2007 and 2023. We collect data on analysts' earnings forecasts, firm fundamental characteristics, and firm financial information from the China Stock Market & Accounting Research (CSMAR) database. Since 2007, all firms listed on Chinese stock markets have been mandated to address corporate rumors by issuing official clarification announcements within two trading days of the rumor's emergence. Therefore, following Jia et al. (2017) and Cai et al. (2023), we conduct a retrospective analysis and manually collect data on corporate rumors based on the official clarification announcements available on the website of the China Securities Regulatory Commission (www.cninfo.com.cn). Utilizing keywords related to the rumors extracted from these clarification announcements, we proceed to retrieve the original corporate rumors via the WiseSearch database and subsequently match them with analyst earnings' forecasts as well as firm characteristics at the firm-year level.[2] This allows us to more precisely eliminate duplicate reports or clarifications of rumors, while also excluding the interference of clarifications related to abnormal stock price fluctuations that are unrelated to the rumors.

Table 1 Panel A presents the sample construction procedure. Our initial sample includes 45,814 firm-year observations among 4566 unique firms, in which we manually collect 4918 pieces of corporate rumors, over the 2007–2023 period. We then exclude firm-years without any analyst following, firms in the financial industry, firm-year observations with missing financial data, and firms with less than three observations. The final sample contains 19,840 firm-year observations and 2405 corporate rumors among 2860 unique firms. Panel B in Table 1 further illustrates the sample distribution by calendar year. It indicates that 190 firms experienced rumors in 2010, whereas only 14 firms were rumored in 2022. Additionally, the overall probability of corporate rumors decreased annually, from 25.51 % in 2008 to 1.28 % in 2023. Overall, 9.51 % of firms in our sample encountered corporate rumors.

Table 1
Sample construction and distribution.

Panel A: Sample construction procedure

Sample period: 2007–2023	# of total rumors	# of firm-years	# of unique firms
Initial sample	4928	45,814	4566
Deleting firm-years without any analyst following	−1842	−19,106	−1261
Deleting firms in the financial industry	−91	−523	−43
Deleting firm-years with missing financial data	−587	−6324	−387
Deleting firms with fewer than three observations	−3	−21	−15
Final sample	**2405**	**19,840**	**2860**

Panel B: Sample distribution by calendar year

Year	# of rumored firms	# of listed firms	% of rumored firms
2007	91	511	17.81 %
2008	162	635	25.51 %
2009	162	841	19.26 %
2010	190	952	19.96 %
2011	186	1003	18.54 %
2012	149	1160	12.84 %
2013	131	1273	10.29 %
2014	155	1440	10.76 %
2015	138	1489	9.27 %
2016	113	1609	7.02 %
2017	127	1554	8.17 %
2018	90	1134	7.94 %
2019	83	1193	6.96 %
2020	49	1162	4.22 %
2021	28	1143	2.45 %
2022	14	1257	1.11 %
2023	19	1484	1.28 %
Total	**1887**	**19,840**	**9.51 % (average)**

This table shows the sample construction and distribution. Panel A details the sample construction procedure. Our initial sample comes from all firms listed in the Chinese A-share market during 2007 and 2023. We exclude firm-years without any analyst following, firms in the financial industry, firm-years with missing financial data, and firms with less than three observations. The final sample contains 19,840 firm-year observations and 2405 corporate rumors among 2860 unique firms. Panel B further reports the sample distribution by calendar year. We identify 1887 rumored firms, accounting for 9.51 % of the full sample.

3.2. Model specification

To investigate the impact of corporate rumors on analysts' earnings forecast dispersion, we construct the baseline model as follows:

$$Dispersion_{i,t+1} = \alpha_0 + \beta_1 RUMOR_{i,t} + \sum \lambda Controls_{i,t} + \text{Year FE} + \text{Firm FE} + \mu_{i,j,t} \quad (1)$$

where the dependent variable $Dispersion_{i,t+1}$ denotes analysts' earnings forecast dispersion for firm i in year $t+1$. Following prior literature (Gao et al., 2021; Liu & Natarajan, 2012), we measure $Dispersion_{i,t+1}$ by the standard deviation of each analyst's last forecast of earnings per share (EPS). The independent variable $RUMOR_{i,t}$ represents the existence of corporate rumors. In line with Cai et al. (2023), we use two measures to ensure robustness: 1) $Dum\_Rumor_{i,t}$, a dummy that equals one if firm i has at least one rumor in year t and zero otherwise; 2) $Total\_Rumors_{i,t}$, which is measured by the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t.

$Controls_{i,t}$ in Eq. (1) represents a series of control variables that may affect analyst forecast dispersion. First, we include firm fundamentals following previous studies (Gao et al., 2021; Liu & Natarajan, 2012; Zhang, 2006): firm size ($Size_{i,t}$), financial leverage ($Lev_{i,t}$), book-to-market ratio ($BM_{i,t}$), and firm age ($Age_{i,t}$). Second, given the close relationship between analysts' earnings forecasts and firm operating performance as well as financial conditions (Gu & Wu, 2003; Jacob, Lys, & Neale, 1999), we control for the effects of earnings loss ($Loss_{i,t}$), return on total assets ($ROA_{i,t}$), sales growth ($Growth_{i,t}$), financial distress denoted by Z-Score ($Z\text{-}Score_{i,t}$) and financial constraint captured by SA index ($SA_{i,t}$). Third, considering the potential impacts of stock performance on analysts' earnings forecasts (Chen, Hong, & Stein, 2001; Doukas et al., 2009; Jiang & Lei, 2023; Johnson, 2004), we include annual stock return ($Return_{i,t}$) and turnover ratio ($Turnover_{i,t}$) in the model. Fourth, as external corporate governance factors are highly associated with analyst forecasts (Behn, Choi, & Kang, 2008; Chiu, Lourie, Nekrasov, & Teoh, 2020; Huang & Mamo, 2016), we further control for institutional shareholding ($Ins\_Hold_{i,t}$), analyst coverage ($Analyst\_Cover_{i,t}$), media news reports ($Media\_News_{i,t}$), and an indicator variable for firms with Big Four auditors ($Big4_{i,t}$). Finally, we include the year fixed effect (Year FE) and firm fixed effect (Firm FE) in the model. To mitigate the impact of extreme values, we winsorize the continuous variables at the top and bottom 1 % levels. Definitions for all variables are provided in Appendix A.

[2] WiseSearch is a commercial news service that collects news reports from more than 1600 printed media and 400,000 online media agencies in mainland China.

3.3. Descriptive statistics

Panel A of Table 2 reports the summary statistics of the main variables. $Dispersion_{i,t+1}$ has a mean value of 0.127, with the median value equal to 0.144, which is comparable to previous findings based on the Chinese A-share firms (Gao et al., 2021; Wang, 2020). The mean value of $Dum\_Rumor_{i,t+1}$ is 0.095, close to that (0.109) reported in Cai et al. (2023), suggesting that 9.50 % of our sample firms encounter corporate rumors. Panel B further presents the results of univariate analysis. The mean value of $Dispersion_{i,t+1}$ in the rumor group ($Dum\_Rumor_{i,t+1} = 1$) is 0.154, whereas that in the non-rumor group ($Dum\_Rumor_{i,t+1} = 0$) is equal to 0.124. Such difference (0.030) is significant at the 1 % level, which provides preliminary evidence of a positive relationship between corporate rumors and analyst forecast dispersion. In addition, it shows that firms with greater leverage, older age, worse performance, better financial conditions, higher stock returns, and greater turnover ratio are more likely to experience rumors. Meanwhile, the rumor group exhibits higher institutional ownership, greater analyst coverage, more extensive media exposure, and a higher probability of Big Four auditing firms. Similar results are corroborated in Appendix B, where we present the correlation analysis of the variables.

Table 2
Descriptive statistics.

Panel A: Summary statistics

Variables	Mean	SD	P25	Median	P75
$Dispersion_{i,t+1}$	0.127	0.144	0.039	0.079	0.157
$Dum\_Rumor_{i,t}$	0.095	0.293	0.000	0.000	0.000
$Total\_Rumors_{i,t}$	0.075	0.242	0.000	0.000	0.000
$Size_{i,t}$	8.630	1.303	7.682	8.462	9.405
$Lev_{i,t}$	0.441	0.198	0.284	0.442	0.593
$BM_{i,t}$	0.605	0.249	0.411	0.596	0.794
$Age_{i,t}$	2.349	0.630	1.946	2.485	2.890
$Loss_{i,t}$	0.048	0.213	0.000	0.000	0.000
$ROA_{i,t}$	0.052	0.050	0.023	0.046	0.077
$Growth_{i,t}$	0.240	0.475	0.021	0.150	0.322
$Z\text{-}Score_{i,t}$	4.944	5.620	1.891	3.159	5.606
$SA_{i,t}$	−3.774	0.251	−3.946	−3.760	−3.597
$Return_{i,t}$	0.295	0.750	−0.203	0.087	0.567
$Turnover_{i,t}$	2.630	1.897	1.211	2.122	3.560
$Ins\_Hold_{i,t}$	0.507	0.249	0.320	0.537	0.699
$Analyst\_Cover_{i,t}$	2.614	0.777	1.946	2.639	3.219
$Media\_News_{i,t}$	5.075	1.143	4.407	5.106	5.776
$Big4_{i,t}$	0.073	0.260	0.000	0.000	0.000
N	19,840				

Panel B: Univariate analysis

Variables	Rumor Group	Non-Rumor Group	Difference tests	
	($Dum\_Rumor_{i,t} = 1$)	($Dum\_Rumor_{i,t} = 0$)	(Rumor Group – Non-Rumor Group)	
	Mean	Mean	Difference	t-value
$Dispersion_{i,t+1}$	0.154	0.124	0.030***	8.65
$Size_{i,t}$	8.675	8.626	0.049	1.58
$Lev_{i,t}$	0.487	0.436	0.051***	10.75
$BM_{i,t}$	0.600	0.606	−0.006	−1.01
$Age_{i,t}$	2.401	2.344	0.057***	3.77
$Loss_{i,t}$	0.060	0.046	0.014***	2.72
$ROA_{i,t}$	0.049	0.053	−0.004***	−3.04
$Growth_{i,t}$	0.257	0.238	0.019*	1.66
$Z\text{-}Score_{i,t}$	4.502	4.990	−0.488***	−3.59
$SA_{i,t}$	−3.715	−3.781	0.066***	10.80
$Return_{i,t}$	0.511	0.273	0.238***	13.18
$Turnover_{i,t}$	2.767	2.616	0.151***	3.30
$Ins\_Hold_{i,t}$	0.545	0.503	0.042***	7.04
$Analyst\_Cover_{i,t}$	2.660	2.610	0.050***	2.69
$Media\_News_{i,t}$	5.328	5.049	0.279***	10.12
$Big4_{i,t}$	0.089	0.071	0.018***	2.87
N	1887	17,953		

This table reports the descriptive statistics of the main variables. Panel A and Panel B show the summary statistics and univariate analysis, respectively. All variables are defined in Appendix A. *** and * indicates significance at the 1 % and 10 % levels, respectively.

4. Empirical tests

4.1. Baseline results

Table 3 examines the impact of corporate rumors on analysts' earnings forecast dispersion to test our main Hypothesis 1. Columns (1) and (2) present the results without any control variable. The coefficients on $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ are 0.030 (t-value = 8.28) and 0.036 (t-value = 7.79), both of which are significantly positive. This suggests that corporate rumors aggravate analyst forecast dispersion for firms with rumors by 24.19 % (0.030/0.124) relative to those without rumors, and one additional standard deviation in $Total\_Rumors_{i,t}$ leads to a 6.05 % (0.036 × 0.242/0.144) increase in analyst forecast dispersion. Hence, the occurrence of corporate rumors is associated with a significantly higher degree of analyst forecast dispersion.

Columns (3) and (4) further report the results with all control variables. The coefficient remains significantly positive for $Dum\_Rumor_{i,t}$ (0.017, t-value = 4.45) and $Total\_Rumors_{i,t}$ (0.019, t-value = 4.09). This suggests that the impact of corporate rumors on analyst divergences is not driven by the firm characteristics potentially associated with analyst forecast dispersion. Overall, Table 3 reveals that corporate rumors exacerbate analyst forecast dispersion, which supports our main Hypothesis 1a.

4.2. Endogeneity concerns

4.2.1. Difference-in-difference tests

The use of a one-period lagged estimation in the baseline model ensures that analysts are able to make decisions after observing the occurrence of corporate rumors, which could alleviate potential endogeneity to some extent. However, our conclusion remains subject to challenges of reverse causality. For instance, firms with greater divergence among analyst forecasts may be more likely targets of corporate rumors. To mitigate such concerns, we employ a DID approach to enhance causal identification.

Since the rapid development of the Internet beginning in 2007, various forms of illegal and criminal activity carried out using information networks have increased steadily in China, with the dissemination of rumors and defamation online being particularly prominent. To provide clear legal interpretations to accurately punish such crimes in judicial practice, the CSPC and CSPP promulgated the *Interpretation of Online Defamation* in September 2013. This interpretation established that defamatory information online reaching actual click-throughs or views exceeding 5000, or shares exceeding 500, should be considered a "serious circumstance" of online defamation, thereby setting out explicit and quantifiable standards for determining criminal liability for this offense.

Because corporate rumors are inherently unofficial information that has not been verified by official sources and are mainly spread through the internet, the *Interpretation of Online Defamation* can serve as an ideal exogenous intervention on the occurrence of rumors. Specifically, rumormongers and propagators may be deterred by the penalty of 5000 views or 500 shares, and therefore avoid creating and spreading false reports related to listed companies, especially defamatory negative news. As shown in Panel B of Table 2, the frequency of corporate rumors after 2013 has decreased annually, indicating that the *Interpretation of Online Defamation* has indeed played a role in suppressing corporate rumors. Even the rumors still exist after 2013, such informal news are more likely to be reasonable inferences based on private information but

Table 3
Baseline results.

Variables	$Dispersion_{i,t+1}$			
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.030***		0.017***	
	(8.28)		(4.54)	
$Total\_Rumors_{i,t}$		0.036***		0.019***
		(7.79)		(4.09)
$Size_{i,t}$			0.023***	0.023***
			(5.24)	(5.24)
$Lev_{i,t}$			0.050***	0.050***
			(3.38)	(3.39)
$BM_{i,t}$			−0.045***	−0.045***
			(−3.63)	(−3.62)
$Age_{i,t}$			−0.068***	−0.068***
			(−7.69)	(−7.69)
$Loss_{i,t}$			0.059***	0.059***
			(7.18)	(7.19)
$ROA_{i,t}$			0.545***	0.545***
			(9.70)	(9.69)
$Growth_{i,t}$			0.008***	0.008***
			(2.93)	(2.93)
$Z\text{-}Score_{i,t}$			0.001	0.001
			(1.27)	(1.28)
$SA_{i,t}$			−0.013	−0.012
			(−0.58)	(−0.57)
$Return_{i,t}$			0.012***	0.012***
			(4.56)	(4.57)
$Turnover_{i,t}$			−0.002*	−0.002*
			(−1.81)	(−1.81)
$Ins\_Hold_{i,t}$			0.040***	0.040***
			(3.26)	(3.27)
$Analyst\_Cover_{i,t}$			0.002	0.002
			(0.98)	(1.00)
$Media\_News_{i,t}$			0.012***	0.012***
			(4.41)	(4.42)
$Big4_{i,t}$			−0.006	−0.006
			(−0.52)	(−0.51)
Cons.	0.124***	0.124***	−0.097	−0.096
	(71.50)	(71.59)	(−1.27)	(−1.25)
Year FE	No	No	Yes	Yes
Firm FE	No	No	Yes	Yes
N	19,840	19,840	19,840	19,840
Adj. R^2	0.004	0.004	0.295	0.294

This table examines the effect of rumors on analyst forecast dispersion based on the baseline model in Eq. (1). $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm *i* in year $t+1$. $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm *i* in year *t*. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm *i* experiences in year *t*. The *t*-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. *** and * indicate significance levels at the 1 % and 10 %, respectively.

less likely to be fabricated and defamatory. In other words, corporate rumors after the *Interpretation of Online Defamation* should be more cautious, thereby weakening their damage to firm information environment.

To investigate the impact of the *Interpretation of Online Defamation* on the rumor effect, we construct a DID model as follows:

$$Dispersion_{i,t+1} = \alpha_0 + \beta_1 RUMOR_{i,t} + \beta_2 RUMOR_{i,t} \times Post2013 + \sum \lambda Controls_{i,t} + \text{Year FE} + \text{Firm FE} + \mu_{i,j,t} \tag{2}$$

where the dependent variable $Dispersion_{i,t+1}$ denotes analysts' earnings forecast dispersion, and the independent variable $RUMOR_{i,t}$ represents the proxies of corporate rumors, i.e., $Dum\_Rumor_{i,t}$, or $Total\_Rumors_{i,t}$. The variable *Post2013* indicates the years following the implementation of the *Interpretation of Online Defamation* in 2013 (including the year 2013 itself). $Controls_{i,t}$ is a series of control variables that are consistent with those included in the baseline model. We also control for the year and firm fixed effects. If the causal relationship between corporate rumors and analyst forecast dispersion holds, we should observe a significant and negative coefficient on β_2, that is, the rumor effect is mitigated by the *Interpretation of Online Defamation*.

Table 4 presents the regression results of the DID tests. In column (1), $RUMOR_{i,t}$ is proxied by $Dum\_Rumor_{i,t}$. The coefficient on $RUMOR_{i,t} \times Post2013$ is significantly negative (coef. = −0.022, *t*-value = −3.04) at the 1 % level. This finding is consistent with our expectation, suggesting that the *Interpretation of Online Defamation* weakens the impact of corporate rumors on analyst disagreement. To ensure the robustness of the DID estimation, we further conduct a parallel trend test in column (2) ($RUMOR_{i,t} = Dum\_Rumor_{i,t}$), where *Year'k'* are dummy variables identifying the year of 'k' and $Year2017^{+}$ represents the years after 2017. It shows that the coefficients on $RUMOR_{i,t} \times Year2010$ to $RUMOR_{i,t} \times Year2013$ are insignificant, whereas the coefficients on $RUMOR_{i,t} \times Year2014$ to $RUMOR_{i,t} \times Year2016$ are significant and negative at the 5 % or 10 % levels. These findings support the parallel trend assumption of the DID setting, suggesting that analyst forecast dispersion among the rumored firms decreases after, rather than before, the year of 2013. Similar reslust also exist in columns (3) and (4), where the independent variable is $Total\_Rumors_{i,t}$. Overall, the findings in Table 4 suggest that

Table 4
Difference-in-difference tests.

Variables	$Dispersion_{i,t+1}$ Dispersion			
	$RUMOR_{i,t} = Dum\_Rumor_{i,t}$		$RUMOR_{i,t} = Total\_Rumors_{i,t}$	
	(1)	(2)	(3)	(4)
$RUMOR_{i,t}$	0.030***	0.033***	0.034***	0.042***
	(4.99)	(3.31)	(4.54)	(3.22)
$RUMOR_{i,t} \times Post2013$	−0.022***		−0.027***	
	(−3.04)		(−2.97)	
$RUMOR_{i,t} \times Year2010$		−0.011		−0.014
		(−0.76)		(−0.82)
$RUMOR_{i,t} \times Year2011$		0.003		−0.013
		(0.12)		(−0.52)
$RUMOR_{i,t} \times Year2012$		−0.004		−0.012
		(−0.25)		(−0.63)
$RUMOR_{i,t} \times Year2013$		−0.025		−0.038**
		(−1.62)		(−2.04)
$RUMOR_{i,t} \times Year2014$		−0.035**		−0.044**
		(−2.45)		(−2.44)
$RUMOR_{i,t} \times Year2015$		−0.032**		−0.039**
		(−2.11)		(−1.98)
$RUMOR_{i,t} \times Year2016$		−0.025*		−0.038**
		(−1.77)		(−2.13)
$RUMOR_{i,t} \times Year2017^{+}$		−0.018		−0.026*
		(−1.44)		(−1.65)
Cons.	−0.091	−0.093	−0.091	−0.092
	(−1.19)	(−1.22)	(−1.19)	(−1.20)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,840	19,840	19,840	19,840
Adj. R^2	0.295	0.295	0.295	0.295

This table reports the results of the DID tests. We employ the *Interpretation of Online Defamation* as an exogenous intervention on the occurrence of rumors. The dependent variable $Dispersion_{i,t+1}$ denotes analysts' earnings forecast dispersion, and the independent variable $RUMOR_{i,t}$ represents the proxies of corporate rumors, i.e., $Dum\_Rumor_{i,t}$ that identifies the occurrence of corporate rumors and $Total\_Rumors_{i,t}$ captures the total number of rumors. The variable *Post2013* indicates the years following the implementation of the *Interpretation of Online Defamation* in 2013 (including the year 2013 itself). *Year'k'* are dummy variables identifying the year of 'k' and $Year2017^{+}$ represents the years after 2017. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The *t*-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

the *Interpretation of Online Defamation* acts as an exogenous shock to effectively alleviate the adverse impact of rumors on the disagreement among analysts, which supports the established causal link between corporate rumors and analyst forecast dispersion.

4.2.2. Two-stage least squares estimations

Another endogeneity issue derives from the correlated omitted variables. We address this concern by performing 2SLS estimations. Following Cai et al. (2023), we employ local lawyer coverage ($Lawyers_{i,t}$), which is calculated as the annual number of practicing lawyers per thousand residents in the province of each firm's headquarter, as the first instrument variable. As argued by Cai et al. (2023), a sound legal system with sufficient legal resources could increase the litigation risk of spreading false news or disclosing inside information, thereby inhibiting the occurrence and appearance of corporate rumors. Besides, we adopt the proportion of the population with a college education or higher ($Education_{i,t}$) in the province where the listed company is located as the second instrumental variable. Intuitively, higher levels of education can not only reinforce legal awareness among residents, but also discourage people from easily believing and spreading rumors. As such, we expect both $Lawyers_{i,t}$ and $Education_{i,t}$ to be negatively related with corporate rumors. Moreover, as macro-level characteristics at the regional level of listed companies, both local lawyer coverage and local education degree are unrelated to the decision-making performance of the analyst community.

Table 5 reports the results for the 2SLS estimations. For the first stage shown in columns (1) and (2), $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ are regressed on the two instrument variables, $Lawyers_{i,t}$ and $Education_{i,t}$, respectively, along with all the control variables included in the baseline model as in Eq. (1). Consistent with our prediction, both instruments have significantly negative effects on corporate rumors. The Wald F-statistics of 32.58 in column (1) and 34.66 in column (2) are both higher than the respective Stock and Yogo (2005) critical value of 16.38 at the 10 % level. This rejects the null condition of weak instruments. In addition, columns (1) and (2) report Sargan's p-values of 0.263 and 0.287, respectively, indicating that the instrument variables satisfy the exclusion restriction.

Columns (3) and (4) reports the results based on the fitted values of $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$. The coefficients on $Dum\_Rumor\_Fit_{i,t}$ and $Total\_Rumors\_Fit_{i,t}$ are 0.017 (t-value = 4.57) and 0.019 (t-value = 4.11), respectively, at the 1 % levels. This suggests that the instrumented corporate rumors still have a significant impact on analyst forecast dispersion. Hence, the evidence from Table 5 reinforces our conclusion and suggests that the positive relationship between corporate rumors and analyst forecast dispersion is unlikely to be driven by other confounding factors that affect both rumors and analyst consensus.

4.2.3. Evidence from propensity-score matched sample

Last, we employ the PSM approach to address potential functional form misspecification due to covariates unbalance (as shown in Panel B of Table 2). Specifically, we estimate a logit regression to predict the probability of the rumor occurrence, and then match each rumored firm with a non-rumored firm in the same industry using the one-to-one nearest neighbor matching method (caliper = 0.01).[3] The covariates involved in matching are consistent with the control variables in the baseline model and contain both industry and year dummy variables. After matching, any difference in analyst forecast dispersion can be more appropriately attributed to the actual existence of corporate rumors than to differences in other firm characteristics.

Table 6 presents the results. Panel A reports the univariate analysis based on the PSM sample. It shows that the mean difference in analyst forecast dispersion remains between the rumor and non-rumor groups.

Table 5
Two-stage least squares estimations.

Variables	First-stage regressions		Second-stage regressions	
	$Dum\_Rumor_{i,t}$	$Total\_Rumors_{i,t}$	$Dispersion_{i,t+1}$	
	(1)	(2)	(3)	(4)
$Lawyers_{i,t}$	−0.088**	−0.072*		
	(−2.24)	(−1.86)		
$Education_{i,t}$	−0.363***	−0.313***		
	(−8.53)	(−8.46)		
$Dum\_Rumor\_Fit_{i,t}$			0.017***	
			(4.57)	
$Total\_Rumors\_Fit_{i,t}$				0.019***
				(4.11)
Cons.	−0.148	−0.184	−0.096	−0.096
	(−0.93)	(−1.29)	(−1.25)	(−1.25)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,751	19,751	19,751	19,751
Adj. R^2	0.084	0.092	0.295	0.294
Wald F-statistics	32.58	34.66		
Sargan's p-value	0.263	0.287		

This table presents the results of the 2SLS estimations. In columns (1) and (2), $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm i in year t. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t. The first instrument variable, $Lawyers_{i,t}$, is calculated as the annual number of practicing lawyers per thousand residents in the province of each firm's headquarter. The second instrument variable, $Education_{i,t}$, represents the proportion of the population with a college education or higher in the province where the listed company is located. In columns (3) and (4), $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm i in year $t+1$. $Dum\_Rumor\_Fit_{i,t}$ and $Total\_Rumor\_Fits_{i,t}$ are the fitted values of $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ based on the regressions in columns (1) and (2), respectively. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The t-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

However, the differences in the 15 control variables between the rumor and non-rumor groups become insignificant after PSM. Thus, the PSM sample achieves covariate balance in the first moment (i.e., mean) for these variables. Panel B re-estimates the baseline model based on the PSM sample. It shows that the coefficients on $Dum\_Rumor_{i,t}$ (coef. = 0.018, t-value = 2.33) and $Total\_Rumors_{i,t}$ (coef. = 0.020, t-value = 2.21) are positive and statistically significant, consistent with the results for our main hypothesis tests in Table 3. This enhances our identification, i.e., our findings are not driven by the bias resulting from the potential functional form misspecification of our linear model.

4.3. Additional robustness checks

To further reinforce our main conclusion, we conduct several robustness checks and report the results in Table 7. Specifically, we first re-estimate the baseline regression using alternative measures of analyst forecast dispersion. Following Johnson (2004) and Zhang (2006), we re-measure analyst dispersion using the standard deviation of each analyst earnings' forecast error (*Dispersion_FE*) calculated by the difference between the forecast EPS and actual EPS deflated by stock price. Also, we employ the divergence in analyst recommendation ratings (*Dispersion_RR*) as another alternative measure of analyst dispersion.[4] Panel

[3] We also use 1:2, 1:3, and 1:4 matching methods and obtain consistent results. To save space, these results are not tabulated in the main text but are available upon request.

[4] The Chinese market has five standard rating levels for analysts, which are buy, accumulate, hold, reduce, and sell. We assign integer values ranging from −2 to 2 for these ratings, with buy assigned a value of 2, accumulate 1, hold 0, reduce −1, and sell −2. A higher score indicates a more optimistic rating from the analyst.

Table 6
Evidence from the propensity-score matched sample.

Panel A: Univariate analysis based on the PSM subsample

Variables	Rumor Group	Non-Rumor Group	Difference tests	
	($Dum\_Rumor_{i,t}$ = 1)	($Dum\_Rumor_{i,t}$ = 0)	(Rumor Group – Non-Rumor Group)	
	Mean	Mean	Difference	t-value
$Dispersion_{i,t+1}$	0.154	0.131	0.023***	4.89
$Size_{i,t}$	8.668	8.690	−0.022	−0.49
$Lev_{i,t}$	0.486	0.491	−0.005	−0.75
$BM_{i,t}$	0.600	0.607	−0.007	−0.83
$Age_{i,t}$	2.401	2.412	−0.011	−0.58
$Loss_{i,t}$	0.060	0.067	−0.007	−0.94
$ROA_{i,t}$	0.049	0.047	0.002	1.13
$Growth_{i,t}$	0.257	0.249	0.008	0.45
$Z\text{-}Score_{i,t}$	4.517	4.326	0.191	1.12
$SA_{i,t}$	−3.716	−3.712	−0.004	−0.52
$Return_{i,t}$	0.502	0.491	0.011	0.38
$Turnover_{i,t}$	2.760	2.736	0.024	0.39
$Ins\_Hold_{i,t}$	0.545	0.555	−0.010	−1.21
$Analyst\_Cover_{i,t}$	2.659	2.672	−0.013	−0.49
$Media\_News_{i,t}$	5.322	5.296	0.026	0.61
$Big4_{i,t}$	0.086	0.089	−0.003	−0.23
N	1873	1873		

Panel B: Regression results using the PSM sample

Variables	$Dispersion_{i,t+1}$	
	(1)	(2)
$Dum\_Rumor_{i,t}$	0.018**	
	(2.33)	
$Total\_Rumors_{i,t}$		0.020**
		(2.21)
Cons.	−0.234	−0.229
	(−1.15)	(−1.13)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	3746	3746
Adj. R^2	0.231	0.230

This table provides the evidence from the PSM sample. Panel A reports the results of univariate analysis, whereas Panel B re-estimate the baseline regression using the PSM sample. $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm i in year $t + 1$. $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm i in year t. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The t-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

Table 7
Additional robustness checks.

Panel A: Alternative measurements of analyst dispersion

Variables	$Dispersion\_FE_{i,t+1}$		$Dispersion\_RR_{i,t+1}$	
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.086**		0.017***	
	(2.39)		(3.03)	
$Total\_Rumors_{i,t}$		0.087*		0.020***
		(1.91)		(2.97)
Cons.	1.083*	1.085*	0.338***	0.339***
	(1.76)	(1.77)	(3.09)	(3.09)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,840	19,840	19,602	19,602
Adj. R^2	0.313	0.313	0.204	0.204

Panel B: Multidimensional fixed effects

Variables	$Dispersion_{i,t+1}$			
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.017***		0.017***	
	(4.53)		(4.52)	
$Total\_Rumors_{i,t}$		0.019***		0.019***
		(4.12)		(4.02)
Cons.	0.002	0.004	−0.026	−0.025
	(0.02)	(0.04)	(−0.23)	(−0.22)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year×Industry FEs	No	No	Yes	Yes
Year×Region FEs	No	No	Yes	Yes
N	19,840	19,840	19,840	19,840
Adj. R^2	0.297	0.296	0.300	0.300

In this table, we conduct several robustness checks. Panel A reports the results with alternative measurements of analyst dispersion. $Dispersion\_FE_{i,t+1}$ is analyst forecast dispersion for firm i in year t, which is calculated by the difference between the forecast EPS and actual EPS deflated by stock price. $Dispersion\_RR_{i,t+1}$ as another alternative measure of analyst dispersion calculated based on the divergence in analyst recommendation ratings for firm i in year t. $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm i in year t. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t. Panel B shows the results with multidimensional fixed effects. In columns (1) and (2), we add industry and region fixed effects in the baseline model. Columns (3) and (4) further control for crossover effects between years and industries, as well as years and regions. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The t-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

A presents the regression results based on these alternative measures of the dependent variable. The coefficients on both $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ are significant and positive, which is consistent with our main finding.

In addition, we include multidimensional fixed effects to control for the influence of omitted variables in multiple dimensions. Specifically, we add industry and region fixed effects in the baseline model (columns (1) and (2) of Panel B) and control for crossover effects between years and industries, as well as years and regions (columns (3) and (4) of Panel B). The significant and positive coefficients on both $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ across the columns suggest that our results are not driven by the omitted variables in the above multiple dimensions.

5. Further research

5.1. Underlying mechanisms

Thus far, we have provided robust evidence that corporate rumors significantly aggravate analyst forecast dispersion. However, the underlying mechanisms of such rumor effect remain unknown. In this section, we examine the channels through which corporate rumors affect analyst forecast dispersion. Specifically, we investigate whether the increased analyst dispersion associated with rumors is due to intensified media disagreement and/or elevated information uncertainty.

5.1.1. Media disagreement

The primary market consequence of rumors is to spark media controversy (Ahern & Sosyura, 2015; Schindler, 2007), and even lead to media bias (Jia et al., 2017). Since media news is an important resource for analysts to obtain information (Engelberg & Parsons, 2011; Hossain et al., 2014), we expect that corporate rumors may hinder analyst consensus by exacerbating media disagreement. To verify this channel, we employ media disagreement ($Media\_Disagreement_{i,t}$) as a mediator and conduct a two-step mediation effect test. $Media\_Disagreement_{i,t}$ is calculated as the standard deviation of the daily media sentiment (i.e., the difference between the daily number of positive media news and negative media news). If the media disagreement channel holds, we should observe a positive relationship between corporate rumors and media sentiment in the first-step regression, as well as a positive impact of media sentiment on analyst forecast dispersion in the-second step regression.

Panel A of Table 8 presents the results of the media disagreement channel tests. Columns (1) and (2) examine the effect of corporate rumors on media disagreement, whereas columns (3) and (4) show the impact of media disagreement on analyst dispersion. The coefficients on $Dum\_Rumor_{i,t}$ (coef. = 0.139, t-value = 4.70) and $Total\_Rumors_{i,t}$ (coef. = 0.160, t-value = 4.41) are significant and positive in columns (1) and (2), suggesting that corporate rumors increase media disagreement. In columns (3) and (4), the significant and positive coefficients on $Media\_Disagreement_{i,t}$ further indicate that media disagreement exacerbates the divergence in analysts' earnings forecasts. Moreover, the Sobel z-statistics reported below columns (3) and (4) are significant at the 1 % levels. This supports the mediating effect of media disagreement in the influence of corporate rumors on analyst divergence.

5.1.2. Information uncertainty

Corporate rumors are inherently unconfirmed and unofficial news that possess a high degree of uncertainty (Rosnow, 1991; Schindler, 2007). Hence, the emergence of rumors necessarily exacerbates information uncertainty, which is also a direct factor contributing to higher disagreement among analyst earnings' forecast (Zhang, 2006). To investigate whether corporate rumors affect analyst forecast dispersion by elevating information uncertainty, we measure information uncertainty faced by analysts using the text analysis techniques. Specifically, we extract the number of uncertainty vocabularies used in analyst earnings' forecast reports issued for firm i in year t and define information uncertainty ($Information\_Uncertainty_{i,t}$) as the average percentage of uncertainty vocabularies.[5] If corporate rumors indeed increase information uncertainty, we should observe an increase in the frequency of uncertainty vocabulary used by analysts in their reports. Moreover, if information uncertainty is a channel of the rumor effect, it should be positively correlated with analyst forecast dispersion.

In Table 8 Panel B, we empirically test the information uncertainty channel of the rumor effect. Columns (1) and (2) examine the impact of corporate rumors on information uncertainty. The coefficients on both $Dum\_Rumor_{i,t}$ and $Total\_Rumors_{i,t}$ are significant and positive, suggesting that corporate rumors increase information uncertainty and thus encourage analysts to use more uncertainty vocabularies in their reports. In the second-step regressions shown in columns (3) and (4), $Information\_Uncertainty_{i,t}$ has positive coefficients at the significant level of 1 %, and the Sobel z-statistics for the of the mediation effect are also significant. This finding verifies our expectation that corporate rumors aggravate analyst disagreement through increasing information uncertainty.

[5] Based on Chinese semantics, we identify uncertainty terms such as "可能" (possibly), "也许" (perhaps), "大概" (probably), "大约" (about), "或许" (maybe), and "有概率" (with probability), etc. These terms all express the idea of possibility and uncertainty in English.

Table 8
Mechanism tests.

Panel A: Media disagreement channel

Variables	$Media\_Disagreement_{i,t}$		$Dispersion_{i,t+1}$	
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.139***		0.016***	
	(4.70)		(4.26)	
$Total\_Rumors_{i,t}$		0.160***		0.018***
		(4.41)		(3.84)
$Media\_Disagreement_{i,t}$			0.007***	0.007***
			(5.49)	(5.51)
Cons.	3.522***	3.531***	−0.123	−0.122
	(5.49)	(5.51)	(−1.61)	(−1.60)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,840	19,840	19,840	19,840
$Adj.\ R^2$	0.487	0.487	0.297	0.296
Sobel z-statistics			3.86***	3.75***

Panel B: Information uncertainty channel

Variables	$Information\_Uncertainty_{i,t}$		$Dispersion_{i,t+1}$	
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.045***		0.014***	
	(3.14)		(4.42)	
$Total\_Rumors_{i,t}$		0.057***		0.016***
		(3.29)		(3.97)
$Information\_Uncertainty_{i,t}$			0.048***	0.048***
			(5.43)	(5.44)
Cons.	3.028***	3.032***	−0.135*	−0.134*
	(9.96)	(9.97)	(−1.74)	(−1.73)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	19,840	19,840	19,840	19,840
$Adj.\ R^2$	0.586	0.586	0.296	0.296
Sobel z-statistics			2.83***	2.92***

In this table, we examine the underlying mechanisms through which corporate rumors affect analyst forecast dispersion. Panels A and B investigate the media disagreement channel and the information uncertainty channel, respectively. $Media\_Disagreement_{i,t}$ is calculated as the standard deviation of the daily media sentiment (i.e., the difference between the daily number of positive media news and negative media news). $Information\_Uncertainty_{i,t}$ is measured by the average percentage of uncertainty vocabularies used in analyst earnings' forecast reports. $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm i in year $t+1$. $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm i in year t. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The t-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

5.2. Cross-sectional analyses

To gain deeper insights into the impact of corporate rumors on analyst earnings' forecast dispersion, we conduct several cross-sectional analyses in this section. As rumor news in fact brings shock to information environment, particularly exacerbating information uncertainty, we are first interested in how information opacity and earnings volatility affect the relationship between corporate rumors and analyst disagreement. Besides, since analysts can establish close communication with listed firms through site visits, we are also curious whether these visits can alleviate the adverse impact of rumors on their consensus. Last, given the role of the news media in creating and spreading rumors, we examine how media ethics affect the rumor effect. Table 9 presents the regression results.

5.2.1. The role of information opacity

The revealed positive correlation between corporate rumors and analyst dispersion implies that rumors disrupt the information environment of the rumored firms. On the one hand, most corporate rumors are actually false news that hinder the market from reaching a consensus. On the other hand, they can directly increase the level of information uncertainty. In this case, a higher degree of information opacity will amplify the damage of rumors to the information environment. As such, we expect that the impact of corporate rumors on analyst forecast dispersion is more significant in firms with greater information opacity.

Panel A in Table 9 compares the impact of corporate rumors on analyst disagreement between firms with high and low information opacity. Information opacity is proxied by absolute discretionary accruals estimated using the performance-matched modified Jones Model (Kothari, Leone, & Wasley, 2005). Firms with high (low) information opacity are defined as those with absolute discretionary accruals greater (less) than the annual industry median. The coefficient on $Dum\_Rumor_{i,t}$ is 0.020 and significant at the 1 % level in the high opacity group (column (1)), which is larger than the coefficient of 0.015 in the low opacity group (column (2)). This difference is also significant at the 10 % level (p-value = 0.062). Similarly, columns (3) and (4) show that the impact of $Total\_Rumors_{i,t}$ in the high opacity group is more significant than that in the low opacity group. These findings also highlight the importance of improving information transparency in mitigating the disruptive impact of corporate rumors on the information environment.

5.2.2. The role of earnings volatility

Prior studies argue that earnings volatility is also an important factor that affect analyst earnings' forecasts (e.g., Chourou et al., 2021; Wang, 2020). High earnings volatility indicates high operational uncertainty and low earnings predictability, making it more difficult for analysts to accurately predict operating cash flows and build a consensus (Johnson, 2004; Zhang, 2006). Drawing on the fundamental volatility theory, a high level of earnings volatility may amplify the uncertainty shock brought by rumors. Hence, we predict that the impact of corporate rumors on analyst forecast dispersion is more pronounced in firms with higher earnings volatility.

Following Frankel and Litov (2009), we measure earnings volatility by the standard deviation of ROA over the past three years. Table 9 Panel B presents the regression results. High (low) volatility firms are classified as those with earnings volatility larger (lower) than the annual industry median. As shown in columns (1) and (2), the coefficient on $Dum\_Rumor_{i,t}$ is 0.020 (t-value = 2.81) among the high volatility group, which is significantly higher than that (0.013) among the low volatility group. This difference is significant at the 5 % level (p-value = 0.024). Meanwhile, columns (3) and (4) show that $Total\_Rumors_{i,t}$ also has a more significant coefficient among firms with high earnings volatility. These results are consistent with our expectation that high earnings volatility amplifies the uncertainty impact of corporate rumors and thus exacerbates the effect of the rumors on analyst disagreement.

5.2.3. The role of analyst-company communication

As information specialists in the capital market, analysts often actively seek out first-hand information through communication with companies to gain insights that are closer to the truth (Mayew, Sharp, & Venkatachalam, 2013; Mikhail, Walther, & Willis, 2007). One of the most effective methods is to conduct site visits to listed companies, during which they can observe operations and facilities, understand corporate culture, and even engage in direct face-to-face communication with managers and employees (Cheng, Du, Wang, & Wang, 2016). Previous studies suggest that analyst site visits can not only improve analyst forecast performance but also promote industry information dissemination (Cheng et al., 2016; Han, Kong, & Liu, 2018; Yang et al., 2020). In this sense, these on-site visit activities should be able to repair the information environment disrupted by corporate rumors. Hence, for firms receiving analyst site visits, the adverse impact of rumors on analyst consensus should be less significant.

To test the above prediction, we manually collect the records of analyst site visits from firm annual reports and the web portal "Hu Dong Yi" for companies listed on the Shenzhen Stock Exchange (SZSE).[6] Panel C of Table 9 examines the difference in the impact of corporate rumors on analyst forecast dispersion between firms with and without analyst site visits. The coefficients on the proxies of corporate rumors are significant and positive in the non-visit group (columns (1) and (3)) but insignificant in the visit group (columns (2) and (4)). Such differences are statistically significant at the 1 % levels. These findings suggest that effective analyst-company communication may help mitigate the impact of corporate rumors on analyst forecast dispersion.

5.2.4. The role of media ethics

News media serve as important information intermediaries in capital markets, playing a crucial role in objectively and accurately conveying financial information to market participants (Bushee et al., 2010). However, media may also fabricate and spread unverified sensational news for their own commercial interests, such as corporate rumors (Jia et al., 2017; Jia et al., 2020). Given the media's critical role in the information network, good media ethics can prevent the dissemination of false information and alleviate the distortion of information environments caused by corporate rumors. As such, the impact of corporate rumors on analyst forecast dispersion should be more evident when media ethics are low.

According to the report from the Chinese General Social Survey (CGSS) in 2013, we score media ethics based on residents' ratings of media ethics in the province where the listed companies are located.[7] We then define regions with low media ethics as those with media ethics scores lower than the median. As shown in Panel D of Table 9, the rumor effect is more prominent for firms located in regions with low media ethics. Specifically, $Dum\_Rumor_{i,t}$ has a significant coefficient equal to 0.021 in the low ethics group (column (1)), whereas it has a coefficient of 0.011 in the high ethics group (column (2)). The empirical p-value below columns (1) and (2) is 0.047, significant at the 5 % level. Meanwhile, the coefficient on $Total\_Rumors_{i,t}$ in column (3) (coef. = 0.023, t-value = 3.90) is also higher than that (coef. = 0.013, t-value = 1.77) in column (4), with a significant p-value of 0.067. Together, these results indicate that the positive relationship between corporate rumors and analyst forecast dispersion is aggravated by low media ethic.

5.3. The impacts of different types of rumors

A rumor, as a form of news, conveys specific signals to the market, such as the story it tells and the emotions it carries. Moreover, a company's response to the rumor can signal its position, potentially shaping market participants' perceptions of the rumor. In this section, we expand

[6] In 2006, the Shenzhen Stock Exchange (SZSE) mandated that listed companies disclose site visit information in their annual reports. By July 2012, the SZSE further required that these firms disclose relevant details about visit activities on the "Hu Dong Yi" platform within two trading days after the visits. However, the Shanghai Stock Exchange (SSE) has yet to implement a similar requirement. Consequently, the sample in this section is limited to listed companies on the SZSE.

[7] The CGSS (official website: http://cgss.ruc.edu.cn/), managed by the Social Survey Research Center and Data Center at Renmin University of China, is a pioneering and comprehensive national continuous academic survey project in China. The 2013 CGSS survey included an evaluation of Chinese residents' opinions on media ethics with the following question presented to respondents: "Do you think the media near you lack social responsibility and report sensational news?" The question provided five answer options ranging from "not serious at all" to "very serious". In this study, we assigned numerical scores of 1 to 5 to the five answer options, with lower scores indicating lower media ethics. It is worth noting that the survey did not cover Tibet, Xinjiang, and Hainan, resulting in the loss of samples from these regions.

Table 9
Cross-sectional analyses.

Panel A: The role of information opacity

Variables	$Dispersion_{i,t+1}$			
	High opacity	Low opacity	High opacity	Low opacity
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.022***	0.013**		
	(3.33)	(2.47)		
$Total\_Rumors_{i,t}$			0.025***	0.015**
			(3.10)	(2.25)
Cons.	−0.164	−0.067	−0.163	−0.066
	(−1.55)	(−0.55)	(−1.53)	(−0.54)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	10,508	9332	10,508	9332
Adj. R^2	0.322	0.287	0.322	0.287
Empirical *p*-value	0.062*		0.045**	

Panel B: The role of earnings volatility

Variables	$Dispersion_{i,t+1}$			
	High volatility	Low volatility	High volatility	Low volatility
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.021***	0.013***		
	(2.81)	(3.44)		
$Total\_Rumors_{i,t}$			0.022***	0.013***
			(2.62)	(3.29)
Cons.	−0.076	−0.112	−0.075	−0.111
	(−0.68)	(−1.03)	(−0.67)	(−1.02)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	10,668	9172	10,668	9172
Adj. R^2	0.298	0.270	0.298	0.270
Empirical *p*-value	0.024**		0.017**	

Panel C: The role of analyst-company communication

Variables	$Dispersion_{i,t+1}$			
	Loose communication	Close communication	Loose communication	Close communication
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.020***	0.006		
	(3.13)	(0.67)		
$Total\_Rumors_{i,t}$			0.021***	0.006
			(2.72)	(0.55)
Cons.	−0.212	−0.010	−0.212	−0.010
	(−1.23)	(−0.06)	(−1.23)	(−0.06)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	6995	6491	6995	6491
Adj. R^2	0.290	0.337	0.289	0.337
Empirical *p*-value	0.006***		0.009***	

Panel D: The role of media ethics

Variables	$Dispersion_{i,t+1}$			
	Low ethics	High ethics	Low ethics	High ethics
	(1)	(2)	(3)	(4)
$Dum\_Rumor_{i,t}$	0.021***	0.011*		
	(4.37)	(1.84)		
$Total\_Rumors_{i,t}$			0.023***	0.013*
			(3.90)	(1.77)
Cons.	−0.095	−0.118	−0.093	−0.117
	(−0.89)	(−1.03)	(−0.88)	(−1.02)
Controls	Yes	Yes	Yes	Yes

(*continued on next page*)

Table 9 (*continued*)

Panel D: The role of media ethics

Variables	$Dispersion_{i,t+1}$			
	Low ethics	High ethics	Low ethics	High ethics
	(1)	(2)	(3)	(4)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	12,237	7101	12,237	7101
Adj. R^2	0.299	0.301	0.298	0.301
Empirical *p*-value	0.047**		0.063*	

This table presents the results of the cross-sectional analyses. Panels A to D examine the roles of information opacity, earnings volatility, analyst-company communication, and media ethics in the relationship between corporate rumors and analyst forecast dispersion. The dependent variable $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm *i* in year $t+1$. $Dum\_Rumor_{i,t}$ is an indicator variable identifying the occurrence of corporate rumors for firm *i* in year *t*. $Total\_Rumors_{i,t}$ is a continuous measurement of corporate rumors calculated as the natural logarithm of 1 plus the total number of rumors that firm *i* experiences in year *t*. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The *t*-statistics in parentheses is based on robust standard errors and clustered at the firm level. The empirical *p*-values below each panel are calculated based on Fisher's permutation tests by bootstrapping 1000 times. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

our investigation by examining the impacts of different types of corporate rumors on analyst dispersion. Specifically, we focus on the differentiated impacts of corporate rumors with varying contents, tones, and clarification manners.

First, we classify rumors based on their content. Given the close relationship between analyst earnings' forecasts and firm cash flows as well as information disclosure, we categorize corporate rumors into operating rumors that related to daily operating cash flows, capital rumors that associated with capital operation cash flows, disclosure rumors that tell stories about firm information disclosure, and other rumors outside of these categories.[8] Second, we employ the text analysis techniques and identify the tone of rumors according to the emotion dictionary of Loughran and Mcdonald (2016), and classify them into negative rumors, neutral rumors, and positive rumors. Third, following Jia et al. (2017), we differentiate between rumors with technical clarifications and those without. Technical clarifications provide detailed evidence to refute the rumors, such as reliable files or pictures, while non-technical clarifications simply deny the rumors.

Table 10 Panel A counts the number and proportion of different types of corporate rumors. Regarding rumor content, our sample included 839 operating rumors (34.89 %), 966 capital rumors (40.17 %), 202 disclosure rumors (8.40 %), and 398 other rumors (16.54 %). In terms of rumor tone, we captured 889 negative rumors, 832 neutral rumors, and 684 positive rumors. We also found that only 401 rumors (16.67 %) were technically clarified by listed companies.

In Panel B of Table 10, we investigate the impacts of different types of corporate rumors on analyst dispersion. The independent variables are measured by the natural logarithm of 1 plus the number of each type of rumors that a firm experiences over the previous year. As shown in column (1), the coefficients on $Operating\_Rumors_{i,t}$ and $Capital\_Rumors_{i,t}$ are significantly 0.025 (*t*-value = 3.19) and 0.012 (*t*-value = 2.27), respectively. Nevertheless, $Disclosure\_Rumors_{i,t}$ and $Other\_Rumors_{i,t}$ have positive but insignificant coefficients. This suggests that corporate rumors related to firms' cash flows, including operating and capital cash flows, have a greater impact on information environment and thus exert more significant effects on analyst disagreement. Column (2) compares the impacts of negative, neutral, and positive rumors. $Negative\_Rumors_{i,t}$ has an insignificant coefficient (coef. = 0.008, *t*-value = 1.12), whereas the coefficients of $Negative\_Rumors_{i,t}$ (coef. = 0.027, *t*-value = 3.24) and $Positive\_Rumors_{i,t}$ (coef. = 0.018, *t*-value = 2.19) are significant and positive. It indicates that analyst consensus is insensitive to negative rumors but shows a more significant response to neutral and positive rumors. In column (3), we examine the impact of rumor clarification. The coefficient on $NonTechClary\_Rumors_{i,t}$ (coef. = 0.020, *t*-value = 3.88) is significant and positive, whereas the coefficient on $TechClary\_Rumors_{i,t}$ (coef. = 0.014, *t*-value = 1.38) is insignificant. This finding means that technical clarifications by listed companies mitigate the disruption caused by rumors to firm information environment, thereby alleviating the impact of corporate rumors on analyst forecast dispersion.

6. Conclusion

Beyond the official disclosures from listed companies and professional financial institutions, the capital market is also filled with various types of rumors. In this study, we manually collect corporate rumors related to Chinese listed firms from 2007 to 2023 and investigate their impact on analyst earnings' forecast dispersion. We show a significant positive relationship between corporate rumors and analyst forecast dispersion, which is supported by various robustness checks, including DID estimations, instrument variable/2SLS regressions, and PSM analysis. We further identify two channels of the rumor effect, i.e., the amplified media disagreement and the increased information uncertainty. Our cross-sectional analyses show that the positive relationship between corporate rumors and analyst forecast dispersion is more evident for firms with greater operational uncertainty, higher information opacity, less analyst communication, and those from regions with lower media ethics. Additional analyses reveal that analyst forecast dispersion is more sensitive to rumors related to firm cash flows (compared with non-cash flow rumors), neutral and positive rumors (compared with negative rumors), and those technically clarified by listed firms (compared with un-technically clarified rumors).

In general, this study reveals the negative externalities of rumors on the information environment through examining cross-sectional analyst forecast dispersion driven by corporate rumors. Our findings not only extend the fundamental volatility theory and imperfect information theory of analyst divergence (Johnson, 2004; Zhang, 2006) but also provide novel empirical evidence for the noise interference argument of corporate rumors (e.g., Ahern & Sosyura, 2015; Cai et al., 2023; Jia et al., 2017; Jia et al., 2020). However, this study contains several limitations. Notably, we do not thoroughly investigate the economic ramifications of rumors amplifying analyst disagreement. Given the critical information intermediary role of analysts in capital markets,

[8] Operating rumors refer to those concerning the daily business activities of a company, such as raw material sourcing, order procurement, marketing strategies, business restructuring, profit and loss, and government contracts, etc. Capital rumors tell stories about debt financing, capital increases, capital injections, mergers and acquisitions, dividend payments, and other capital-related activities. Disclosure rumors concern concealment of significant accidents, profit whitewashing, false disclosure, financial fraud, disclosure of insider information, and other disclosure-related issues.

Table 10
The impacts of different types of rumors.

Panel A: Statistics of various types of rumors

Types	# of rumors	% of rumors
Classification by rumor content		
Operating rumors	839	34.89 %
Capital rumors	966	40.17 %
Disclosure rumors	202	8.40 %
Other rumors	398	16.54 %
Classification by rumor tone		
Negative rumors	889	36.96 %
Neutral rumors	832	34.59 %
Positive rumors	684	28.45 %
Classification by rumor clarification		
Rumors with technical clarification	401	16.67 %
Rumors without technical clarification	2004	83.33 %
Total rumors	**2405**	**100.00 %**

Panel B: Regression results

Variables	$Dispersion_{i,t+1}$		
	(1)	(2)	(3)
$Operating\_Rumors_{i,t}$	0.025***		
	(3.19)		
$Capital\_Rumors_{i,t}$	0.012**		
	(2.27)		
$Disclosure\_Rumors_{i,t}$	0.013		
	(0.98)		
$Other\_Rumors_{i,t}$	0.016		
	(1.51)		
$Negative\_Rumors_{i,t}$		0.008	
		(1.21)	
$Neutral\_Rumors_{i,t}$		0.027***	
		(3.24)	
$Positive\_Rumors_{i,t}$		0.018**	
		(2.19)	
$TechClary\_Rumors_{i,t}$			0.014
			(1.38)
$NonTechClary\_Rumors_{i,t}$			0.020***
			(3.88)
Cons.	−0.097	−0.094	−0.096
	(−1.26)	(−1.23)	(−1.25)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	19,840	19,840	19,840
$Adj.\ R^2$	0.294	0.294	0.294

This table examines the impacts of difference types of rumors on analyst forecast dispersion. Panel A presents the statistics of different types of rumors. Panel B further reports the regression results. The dependent variable $Dispersion_{i,t+1}$ represents analyst forecast dispersion for firm i in year $t+1$. The independent variables are measured by the natural logarithm of 1 plus the number of each type of rumors that a firm experiences over the previous year. To save space, we include the control variables that are consistent with those in the baseline model but do not report their impacts in this table. The t-statistics in parentheses is based on robust standard errors and clustered at the firm level. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % levels except for the dummy variables. ***, **, and * indicate significance levels at the 1 %, 5 %, and 10 %, respectively.

future research could further examine whether analyst disagreement under corporate rumor shocks constitutes a significant factor contributing to stock mispricing.

Moreover, the findings of this study offer practical insights for market participants to evaluate the adverse impacts of media hype. Investors and analysts should rationally assess the information validity of corporate rumors, even if they have been clarified by listed companies. For managers, they should provide detailed evidence to technically clarify corporate rumors, thereby alleviating their disruption to firm information environment. Last, regulators should strengthen their supervision and punishment of the creation and dissemination of false report to maintain the information order of the capital market.

Declaration of competing interest

None.

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Appendix A. Variable definition

Variables	Definition
Variables for analyst earnings forecast dispersion	
$Dispersion_{i,t+1}$	Following Liu and Natarajan (2012) and Gao et al. (2021), analyst forecast dispersion is measured as the standard deviation of analyst earnings' forecast on firm i's EPS in year $t + 1$.
$Dispersion\_FE_{i,t+1}$	Following Johnson (2004) and Zhang (2006), we also measure analyst forecast dispersion using the standard deviation of analyst earnings' forecast error, which is the difference between firm i's forecast EPS and actual EPS deflated by stock price.
$Dispersion\_RR_{i,t+1}$	Following Gao et al. (2021), we further employ the standard deviation of analyst recommendation rating scores for firm i in year $t + 1$ as an alternative measure of analyst forecast dispersion.
Variables for corporate rumors	
$Dum\_Rumor_{i,t}$	Following Cai et al. (2023), *Dum_Rumor* is defined as a dummy that equals 1 if firm i experiences at least one piece of rumor in year t, and 0 otherwise.
$Total\_Rumors_{i,t}$	Following Cai et al. (2023), total corporate rumors is measured by the natural logarithm of 1 plus the total number of rumors that firm i experiences in year t.
$Operating\_Rumors_{i,t}$	Rumors related to cash flows from daily operation, which is measured by the natural logarithm of 1 plus the annual number of rumors that related to firm i's daily operating cash flows in year t.
$Capital\_Rumors_{i,t}$	Rumors related to cash flows from capital operation, which is measured by the natural logarithm of 1 plus the annual number of rumors that related to firm i's capital operation cash flows in year t.
$Disclosure\_Rumors_{i,t}$	Information disclosure rumors, which is measured by the natural logarithm of 1 plus the annual number of rumors that related to firm i's information disclosure issues in year t.
$Excutive\_Rumors_{i,t}$	Executive rumors measured by the natural logarithm of 1 plus the annual number of rumors that related to firm i's executive gossips in year t.
$Other\_Rumors_{i,t}$	Other rumors measured by the natural logarithm of 1 plus the annual number of other types of rumors that unrelated to firm i's daily operating, capital operation, information disclosure, and executive gossips in year t.
$Negative\_Rumors_{i,t}$ ($Neutral\_Rumors_{i,t}$ or $Positive\_Rumors_{i,t}$)	Negative (neutral or positive) rumors measured by the natural logarithm of 1 plus the annual number of firm i's negative (neutral or positive) rumors in year t.
$Technical\_Rumors_{i,t}$ ($NonTechnical\_Rumors_{i,t}$)	Technical (non-technical) clarified rumors measured by the natural logarithm of 1 plus the annual number of rumors technically (non-technically) clarified by firm i in year t.
Control variables	
$Size_{i,t}$	Firm size measured by the natural logarithm of total market value for firm i in year t.
$Lev_{i,t}$	Firm leverage measured by total debt divided by total assets for firm i in year t.
$BM_{i,t}$	Book-to-market ratio measured by book value of equity divided by market value of equity for firm i in year t.
$Age_{i,t}$	Firm age measured by the natural logarithm of 1 plus the years listed on the stock exchange for firm i in year t..
$Loss_{i,t}$	Earnings loss, a dummy variable equal to 1 if firm i's earnings are negative and 0 otherwise in year t.
$ROA_{i,t}$	Return on assets measured as net income over total assets for firm i in year t.
$Growth_{i,t}$	Sales growth measured by the change in sales revenue divided by lagged sales revenue for firm i in year t.
$Z\text{-}Score_{i,t}$	Financial distress measured by the Z-Score for firm i in year t.
$SA_{i,t}$	Financing constraint measured by the SA index for firm i in year t.
$Return_{i,t}$	Firm i's annual stock returns for shares listed in the Chinese A-share market in year t.
$Turnover_{i,t}$	Turnover ratio measured as the trading volume divided by total number of shares for firm i in year t.
$Ins\_Hold_{i,t}$	Institutional ownership measured as shares held by institutional investors divided by total number of shares for firm i in year t.
$Analyst\_Cover_{i,t}$	Analyst coverage measured as the natural logarithm of 1 plus the number of analysts following firm i in year t.
$Media\_News_{i,t}$	Media news reports measured as the natural logarithm of 1 plus the number of media news associated with firm i in year t.
$Big4_{i,t}$	Dummy that equals 1 if the firm is audited by a Big-4 audit firm, and 0 otherwise.
Other variables	
Post2013	A dummy variable that indicates the years following the implementation of the *Interpretation of Online Defamation* in 2013 (including the year 2013 itself).
Year'j'	A dummy variable that identifies the year '*j*'.
$Year2017^{+}$	A dummy variable that represents the years after 2017 (including the year 2017 itself).
$Lawyers_{i,t}$	Local lawyer coverage, which is calculated as the annual number of practicing lawyers per thousand residents in the province where the listed company is located.
$Education_{i,t}$	Local education degree, which is measured by the proportion of the population with a college education or higher in the province where the listed company is located.
$Media\_Disagreement_{i,t}$	Media dispersion measured by the standard deviation of the daily media sentiment index for firm i in year t.
$Information\_Uncertainty_{i,t}$	Information uncertainty measured by the average percentage of ambiguous words used in analyst reports issued for firm i in year t.

Appendix B. Correlation analysis

This table reports the correlations of the main variables. The top right (bottom left) provides the Spearman (Pearson) correlation coefficients. All variables are defined in Appendix A and winsorized by year at the top and bottom 1 % level except for the dummy variables. The numbers in bold are statistically significant at the 1 % or 5 % levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)$Dispersion_{i,t+1}$	1	**0.109**	**0.109**	**0.068**	**0.070**	**−0.067**	**−0.087**	−0.003	**0.165**	**0.130**	**0.026**	**0.091**	**0.098**	**0.058**	**0.098**	**0.257**	**0.138**	**0.040**
(2) $Dum\_Rumor_{i,t}$	**0.061**	1	**0.999**	0.011	**0.078**	−0.005	**0.023**	**0.019**	**−0.032**	0.001	**−0.044**	**0.076**	**0.057**	**0.031**	**0.048**	**0.019**	**0.076**	**0.020**
(3) $Total\_Rumors_{i,t}$	**0.060**	**0.960**	1	0.011	**0.078**	−0.005	**0.024**	**0.019**	**−0.031**	0.002	**−0.043**	**0.076**	**0.057**	**0.030**	**0.048**	**0.019**	**0.077**	**0.020**
(4)$Size_{i,t}$	**0.082**	0.011	0.012	1	**0.506**	**0.493**	**0.584**	**−0.020**	**−0.161**	**−0.041**	**−0.499**	**−0.255**	**−0.104**	**−0.451**	**0.345**	**0.251**	**0.384**	**0.280**
(5)$Lev_{i,t}$	**0.055**	**0.076**	**0.078**	**0.507**	1	**0.431**	**0.353**	**0.075**	**−0.455**	**0.016**	**−0.792**	**−0.035**	**0.019**	**−0.130**	**0.236**	**−0.028**	**0.114**	**0.105**
(6)$BM_{i,t}$	**−0.066**	−0.007	−0.010	**0.527**	**0.427**	1	**0.241**	**0.014**	**−0.377**	**−0.119**	**−0.768**	0.001	**−0.356**	**−0.255**	**0.118**	**−0.178**	**−0.050**	**0.151**
(7)$Age_{i,t}$	**−0.073**	**0.027**	**0.029**	**0.562**	**0.368**	**0.231**	1	**0.029**	**−0.171**	**−0.172**	**−0.276**	**−0.498**	**−0.025**	**−0.367**	**0.286**	−0.005	**0.176**	**0.169**
(8)$Loss_{i,t}$	**0.015**	**0.019**	**0.019**	**−0.018**	**0.080**	0.012	**0.034**	1	**−0.366**	**−0.193**	**−0.120**	**−0.027**	**−0.051**	**0.045**	**−0.069**	**−0.119**	**0.018**	0.000
(9)$ROA_{i,t}$	**0.154**	**−0.022**	**−0.020**	**−0.119**	**−0.417**	**−0.355**	**−0.135**	**−0.492**	1	**0.269**	**0.564**	**0.021**	**0.102**	**−0.057**	**0.086**	**0.346**	−0.008	0.010
(10)$Growth_{i,t}$	**0.117**	0.012	0.013	−0.001	**0.054**	**−0.049**	**−0.065**	**−0.124**	**0.174**	1	**0.074**	**0.105**	**0.095**	**0.078**	**0.020**	**0.157**	−0.002	**−0.042**
(11)$Z\text{-}Score_{i,t}$	**0.034**	**−0.025**	**−0.025**	**−0.354**	**−0.617**	**−0.599**	**−0.183**	**−0.051**	**0.414**	−0.013	1	0.007	**0.172**	**0.139**	**−0.147**	**0.168**	0.008	**−0.110**
(12)$SA_{i,t}$	**0.055**	**0.076**	**0.073**	**−0.154**	**−0.035**	0.004	**−0.472**	**−0.026**	**0.020**	**0.041**	**0.039**	1	**0.068**	**0.150**	**0.067**	**0.068**	**−0.050**	**0.036**
(13)$Return_{i,t}$	**0.115**	**0.093**	**0.092**	**−0.128**	**0.042**	**−0.346**	**−0.037**	**−0.039**	**0.097**	**0.125**	**0.147**	**0.116**	1	**0.342**	**0.067**	**0.061**	**0.016**	**−0.014**
(14)$Turnover_{i,t}$	**0.035**	**0.023**	**0.021**	**−0.419**	**−0.134**	**−0.256**	**−0.379**	**0.034**	**−0.060**	**0.068**	**0.101**	**0.154**	**0.361**	1	**−0.354**	**−0.191**	**−0.118**	**−0.182**
(15)$Ins\_Hold_{i,t}$	**0.066**	**0.050**	**0.049**	**0.357**	**0.250**	**0.120**	**0.296**	**−0.067**	**0.095**	**0.045**	**−0.085**	**0.051**	**0.084**	**−0.329**	1	**0.232**	**0.093**	**0.223**
(16) $Analyst\_Cover_{i,t}$	**0.164**	**0.019**	**0.017**	**0.264**	**−0.030**	**−0.177**	−0.003	**−0.120**	**0.333**	**0.062**	**0.124**	**0.069**	**0.038**	**−0.184**	**0.226**	1	**0.360**	**0.135**
(17)$Media\_News_{i,t}$	**0.114**	**0.072**	**0.074**	**0.430**	**0.104**	**−0.042**	**0.174**	**0.019**	**0.029**	−0.002	**0.062**	**−0.058**	**−0.084**	**−0.102**	**0.078**	**0.366**	1	**0.138**
(18)$Big4_{i,t}$	**0.029**	**0.020**	**0.019**	**0.324**	**0.103**	**0.155**	**0.162**	0.000	**0.016**	**−0.033**	**−0.078**	**0.048**	**−0.022**	**−0.152**	**0.219**	**0.136**	**0.155**	1

Data availability

Data will be made available on request.

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