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Media Platforms and Stock Performance:
Evidence From Internet News

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ABSTRACT

Media-aware stock performance has been well recognized in recent studies. Previous research, however, focused on the content influence of the media, ignoring the manner in which the media is delivered. Based on the trust theory, this study argues that the media platforms, as media distribution vehicles and trust endorsement for news, are themselves influential on the stock market. This paper collected news data from seven Chinese mainstream media platforms and classified them into official, professional, and mass media platforms to investigate the impact of different platforms. The authors find that high official and professional media coverage predict increased abnormal returns, while high mass media coverage predicts the opposite. In addition, this paper systematically explores the mechanism of media platforms on stock performance from the perspectives of platform content, audience, and publication timeliness. The findings include that investors' attention to media platforms has a moderating effect on the stock performance, and such an effect is more salient in bear markets.

KEYWORDS

Mass Media, Media Platforms, Official Media, Professional Media, Stock Market

1. INTRODUCTION

The interaction between news and stock performance is a long-standing research topic in the price discovery of financial markets (Calomiris & Mamaysky, 2019; Chan, 2003; Tetlock, 2007). Cutler et al. (1988) is one of the earliest studies to examine the news effect on stock prices. It first reveals that macroeconomic news related to fundamentals has little impact on the stock market and that there is no direct link between political macroeconomic news and stock returns. Tetlock (2007) uses text analysis to quantify the news in Wall Street Journal and finds that news articles with high pessimism increase the downward pressure on the market. Later on, the influence of news on the stock market has been well recognized by a number of scholars (Tetlock et al., 2008; Li et al., 2017). Calomiris and Mamaysky (2019) even find that news could forecast the national economic trends in their study of 51 countries. These studies focus on the impact of news content on the stock market without distinguishing between their source channels (media platforms). However, media platforms provide

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a trust endorsement of the impact of news content on the stock market. Exploring the endorsement function of media platforms is important to further understand the underlying mechanisms of how news affects the stock market.

The guru effect in management literature (Sperber, 2010) and the endorsement or guarantee effect in finance literature (Guiso et al., 2008; Pevzner et al., 2015) have been widely studied. In the process of disseminating information, media platforms also have the responsibility of fostering trust and reducing information asymmetry (Fletcher & Park, 2017). The same words will have a more significant impact if they come from a guru rather than ordinary people. The news is analogous to a speaker's words, and the media platform performs the function of the speaker. It is of great interest to understand the role of media platforms in stock performance. In the earlier stage, most financial news is published on official platforms like Securities Times and professional platforms like Eastmoney. With the advancement of the Internet, an increasing number of news is published online on mass media platforms like Sina. In this study, we investigate the effects of various media platforms in terms of these three media types, that is, official, professional, and mass media platforms.

Evidence indicates that the media platform serves the trust endorsement for news (Fletcher & Park, 2017). It is important to verify whether the influence of a media platform comes from its capacity to endorse or the news content it releases. In this sense, it should figure out if there are significant content differences between various financial media platforms. Some studies have demonstrated that platforms are prone to biased reporting due to selective reporting in an atmosphere of information overload (Garz, 2014; Sigelman, 1973; Zhu & Dukes, 2015). However, it has also been noted that in the Internet environment, the cost of information distribution is reduced, platforms weaken the filtering function of information in pursuit of timeliness and attention, and the media have convergent coverage (Donsbach, 2004; Lee & Tandoc, 2017;). In this study, we investigate the convergence of news articles on different financial media platforms in terms of the stocks covered and the news content. In addition, we select the subsamples of the same news from several media platforms and discover that the influence of media platforms still exists. These results corroborate our hypothesis that the role of media platforms in endorsement can influence stock performance in a manner that is independent of their news content.

The release time of news is another crucial feature that can cause an inconsistent influence even for the same event (Huang et al., 2020; Tetlock, 2011). It is possible that the effect of press releases decays over time, and initial news typically has a more significant impact than stale news. Similarly, we should consider if this media platform's influence stems from the release time of news on the platforms. For instance, the official media has some exclusive advantages for policy distribution. In evaluating the effect of release time on stock performance, we identify the earliest releases and construct the release time period for the same news. In contrast, we find no evidence that the platform's capacity to gather and analyze news results in a significant variation in the release time of the same news, and the hypothesis that the impact of media platforms on stock performance is related to the release time of their news is rejected by statistical tests.

Following our analysis of news content and release timing, we argue that the media platforms' endorsement ability may be attributed to the audiences they attract through disseminating information. According to the theory of limited attention (Bernard & Thomas, 1989; Kahneman, 1973; Kohlhas & Walther, 2021; Peng & Xiong, 2006), investors can react to only partial information in the stock market and they have an uneven capacity or belief to absorb and comprehend information. As a result, investors will gradually develop their preferences for media platforms. For example, professional investors are more likely to search for information on media platforms such as Eastmoney, which are geared toward financial professionals. Ordinary investors prefer to obtain information from mass media platforms such as Sina, which offers a more diversified range of information. In addition, the Internet media platform has converted the initial one-way information transmission into a two-way engagement with the audience. Audiences are willing to select media platforms that satisfy their informational requirements, and the platform can obtain a comprehensive user profile to push information more accurately. Audiences on Internet media platforms are sticky and precisely positioned. To assess the impact of media platforms on stock performance due to different audiences, we construct retail and institutional investors to describe the audiences of the stock market as in previous studies (Basak & Pavlova, 2013; Kumar & Lee, 2006; Neupane & Poshakwale, 2012). These tests demonstrate that institutional investors' attention and ownership enhance the stock performance of high-authority media platforms. We suggest the extent to which media platforms influence stock performance through the key mechanism of audiences.

In sum, investors receive financial news through various types of Internet media platforms. We divide Internet media platforms into official media (Phoenix and Securities Times), professional media (Hexun, Tonghuashun, and Eastmoney), and mass media (Sina and Tencent). In addition, we use the Fama-French three-factor model to estimate abnormal returns as a proxy for stock performance. We conclude that (1) stocks with more coverage from official and professional media have a significant positive effect on stock performance, but more coverage from mass media has the opposite effect; (2) the association between media platforms and stock performance may be driven by the audiences they attract in our analysis; (3) the influence of media platforms on stock performance is more significant in the subsamples of bear markets. Our main findings reveal that media platforms act as the trust endorsement for the impact of news on stocks through trust theory and the limited attention hypothesis, which contribute to and advance the understanding of how media platforms affect stock performance.

The remainder of this paper is organized as follows. Section 2 presents a literature review and hypothesis development on the impacts of media platforms. Section 3 describes the empirical data and variables applied. Section 4 presents the empirical results and robustness checks, and Section 5 concludes.

2. LITERATURE AND HYPOTHESES

2.1 Media Platforms

Prior studies indicate that the media plays a vital price discovery role in the stock market by exposing key information or affecting investor sentiment (Chan, 2003; Fang & Peress, 2009; Tetlock, 2007; Chen et al., 2021). Due to technical limitations, media influence is represented as a Boolean or numeric value in the pilot research. For example, Chan (2003) adopts dummy variables to describe the news influence and finds stocks with public news that would predict momentum or strong drift. Fang and Peress (2009) count the weighted sum of news articles and discover that the stock with more information earns lower returns. Evidently, a simple method of quantifying media influence is incapable of capturing the word power of news. Later, Tetlock (2007) takes a further step by analyzing the pessimism in news articles and finds that negative news has downward pressure on the stock price. However, these studies equate the influence of news with media platforms and provide little insight into the capacity of media platforms to cause inconsistent movements in stock prices. Sperber (2010) initially demonstrates the "guru effect" and explains it through the manifestation of trust (Glaser et al., 2000) and authority (Dessein, 2002). Media platforms are the trust endorsement of news, which can indicate the news authorities. Trust theory suggests that endorsement can effectively alleviate information asymmetry, and the media platform is an important trust endorsement by affecting investor attention or trust (Courtney et al., 2017).

We relate the studies of endorsement (Knittel & Stango, 2014) and the "guru effect" (Sperber, 2010) to consider the impact of media platforms on the stock market. Based on trust theory (Fletcher & Park, 2017; Guiso et al., 2008; Pevzner et al., 2015; Rouibah et al., 2022; Sohaib, 2021), platforms with high endorsement and authority have more influence in the stock market (Fletcher & Park, 2017). The market transfers its trust in media platforms into trust in the coverage of stocks, which can generate abnormal stock performance. The official media is a platform for policymakers to publish and disseminate policy. It is mainly used to disseminate authoritative information on policies. The professional media is mainly for the interpretation of policies and information by experts, which can convey the views of some professional institutions. The mass media tends to be highly opinionated and controversial (Price et al., 2002), which can rely on its social media outlets to expand its dissemination and enhance its influence. More precisely, official and professional media platforms attract more trust from investors, which is associated with stock performance. Under these conditions, we posit the first hypothesis:

H1: The type of media platforms affects stock performance.

2.2 News Content and Platforms

Research on news content for media platforms can be categorized into two groups. Several studies have found that differences in media positions (Gunther et al., 2001; Jacobs et al., 2021), opinions (Zhu & Dukes, 2015), and organizational structures (Sigelman, 1973) can lead to biased or selective reporting of the same event. Sigelman (1973) identifies reporting bias and relates it to organizational structure and management procedures. As the practice develops, scholars begin to recognize that external variables can contribute to media reporting bias. Garz (2014) demonstrates that journalistic knowledge and competence also play a role in determining reporting bias. Zhu and Dukes (2015) point out that commercially operated media tend to report views or content that cater to commercial interests. However, some researchers also provide sufficient evidence on news convergence across media platforms (Donsbach, 2004; Lee & Tandoc, 2017; Whitney & Becker, 1982; Rivera-Trigueros & Olvera-Lobo, 2021). For instance, Whitney and Becker (1982) find that the coverage of small newspapers is influenced by the New York Times. Donsbach (2004) provides evidence that journalists share news through social networks. We contend that convergent content will grow increasingly prominent, especially on Internet platforms (Wang et al., 2021). Consistent with this perspective, an empirical survey by Lee and Tandoc (2017) further reveals that online feedback drives news focus and content.

Considering these contradictory arguments, we examine whether the impact of media platforms on stock performance is related to their news content. On the one hand, reporting bias implies that the influence may stem from the news content on media platforms. In the stock market, Internet media platforms focus on multiple companies and stocks or publish differentiated news content, which can be observed in similar results as the platform effect. On the other hand, coverage convergence shows that media platforms face similar company information and stock price fluctuations. The information is published expeditiously on media platforms and reflected by stock price, which implies that the differentiated stock performance is not the result of their news content. Consequently, we provide our second set of hypotheses:

H2(a): The impact of media platforms on stock performance is related to their news content.
H2(b): The impact of media platforms on stock performance is not related to their news content.

2.3 Audiences and Platforms

The influence of media platforms depends on the information dissemination to the specific audience they attract. First, the limited attention is based on the argument that investors can only respond to a portion of information (Bernard & Thomas, 1989; Kahneman, 1973; Kohlhas & Walther, 2021; Peng & Xiong, 2006). Second, the platform can identify the most suitable investors based on the algorithm (Shin, 2021; Xing et al., 2021), which may generate a specific preference of investors (Badham & Mykkänen, 2022; Bruns, 2012; Kim, 2016).

The concept of limited attention originates in psychology. Kahneman (1973) explains it as the limited ability of individuals to process multiple tasks. Later, limited attention was subsequently applied to many financial issues, such as corporate disclosure, portfolio returns, and stock performance.

Bernard and Thomas (1989) conclude that investors tend to accept simple, salient, and easily communicated information and underrepresent complex information. Peng and Xiong (2006) find that limited attention makes investors tend to choose simple decision principles. Kohlhas and Walther (2021) propose asymmetric attention and explain the under responsiveness to new information. Theoretically, media platforms also have content difficulty, expression, and presentation. The audience can choose platforms based on these patterns.

Simultaneously, media platforms have the ability to disseminate, frame, and exert influence on their audience. Bruns (2012) develops the concept of "producers" and asserts that the audience fulfills the roles of the media producer and consumer at the same time. These shifting roles increase the stickiness of platforms and audiences. It is quickly confirmed by Kim (2016), who illustrates that despite the existence of various media platforms, representative consumers of each medium differ significantly in terms of user background, interest preferences, and knowledge. With the growth of interactive, user-centric, Internet-based platforms, the relationship between platforms and audiences has strengthened. Badham and Mykkänen (2022) show that current media have become more platform-dependent and utilize social media to boost audience contact. Consequently, media platforms play a critical role in adapting to their audiences.

In the stock market, investors are the main audience for media platforms. De Long et al. (1990) divide traders into noise traders and rational arbitrageurs by using the theoretical model. Noise trades perform a random belief about future stock performance, and rational arbitrageurs show Bayesian beliefs with statistical methods. In empirical research, scholars usually use retail and institutional investors to describe the two types of traders (Basak & Pavlova, 2013; Kumar & Lee, 2006; Neupane & Poshakwale, 2012). Institutional investors are more inclined to use platforms with strong expertise, more considerable capital, and faster response. Retail investors have weak information interpretation skills and prefer to read simple and widely disseminated news. From this point of view, institutional investors can quickly translate their information advantage into stock prices, while retail investors are not immediately reflected in stock performance due to disagreements. In addition, the advancement of Internet technology can target audiences more precisely. Media platforms would further publish content that meets the preferences of audiences. Therefore, we propose our third hypothesis:

H3: The impact of media platforms on stock performance varies with audiences.

2.4 Timeliness and Platforms

The timing plays a vital role in each theory of media-aware stock performance (Huang et al., 2020; Tetlock, 2011). In fact, information theory suggests that in an efficient market, new information is instantly reflected in the stock price and becomes stale information, which shows no effect on stock performance (Tetlock, 2011). Furthermore, Huang et al. (2020) define "news clusters" and provide evidence that institutional investors contribute to price efficiency. Because media platforms are the carriers of news, there is a significant concern about whether the impact of media platforms is a result of new or stale information. Platforms with informational advantages can report breaking news first and generate an effect. Without an information advantage, platforms may only post outdated news. If this hypothesis holds, it can be expected that incoming news predicts abnormal returns while stale news has little effect on stock performance.

However, the rapid release and dissemination of online media platforms have steadily diminished the release time period for the same event. Specifically, some scholars have focused on explaining information propagation through field theory in physics (Bucher, 2020; Shang et al., 2017). Shang et al. (2017) argue that investors' sharing behavior accelerates information dissemination, and the release time difference on the Internet diminishes. Bucher (2020) states that algorithms make information available in real time and produce a new temporal regime. From this perspective, there is little substantial variation across platforms regarding the release time of news, and it could suggest that the impact of media platforms is not driven by their news timeliness. Therefore, we propose our fourth set of hypotheses:

H4(a): The impact of media platforms on stock performance is related to the release time of their news.
H4(b): The impact of media platforms on stock performance is not related to the release time of their news.

3. DATA AND VARIABLES

This section focuses on the data and variables we use. First, we classify media platforms into official, professional, and mass media. Then, we calculate abnormal returns for each stock during the news release period. Finally, we consider other controls that may affect stock returns.

3.1 Measuring the Media Platforms

We focus on the top seven financial portal sites in China (Phoenix, Securities Times, Hexun, Tonghuashun Eastmoney Sina, and Tencent) and divide them into three media platforms. Table 1 describes the details of each portal site. In addition, AI Crawler collects 56,095 news items from 2,727 listed companies reported from January 1, 2015, to December 31, 2018. There are 4,176 news items from official media, 30,759 news items from professional media, and 21,160 news items from mass media. Then, we obtain 23,561 matches from daily abnormal returns (Section b). Fig. 1 shows the average coverage of three media platforms.

3.2 Measuring Abnormal Returns

According to financial economics, the abnormal return (AR) refers to the difference between the actual return and the expected return of stocks. The measure also reflects the return on stocks and the relationship between stocks and the market. The AR can illustrate the effect and direction of factors that influence stock prices.

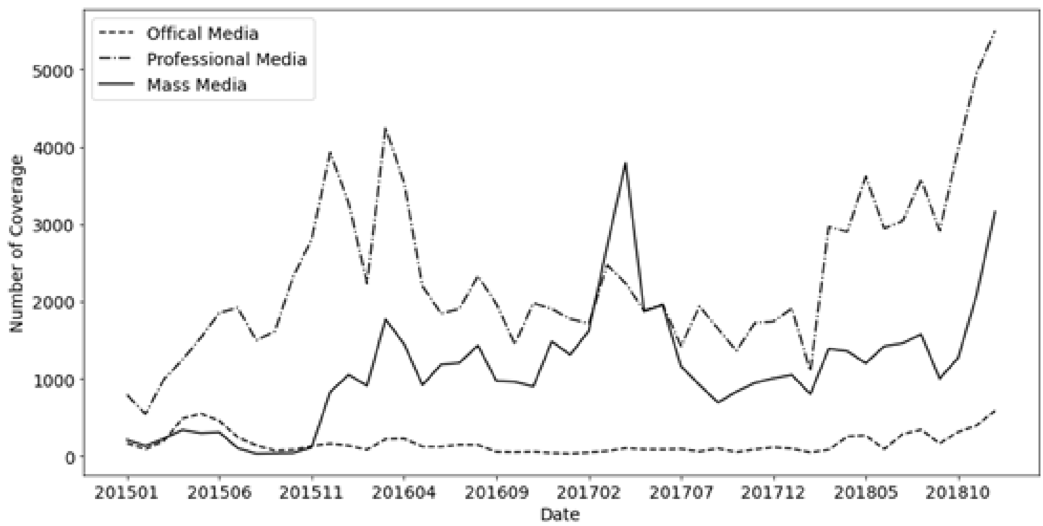
The release of news by media platforms is regarded as an event that causes abnormal returns. To avoid mutual interference caused by overlapping events, we keep the period greater than 14 days of coverage for the same listed company. The estimation period is set as a time window of [-160, -22] days (Boehmer et al., 1991; Cowan, 1992). In addition, the event window of [-10, +10] trading days around the news release is chosen to estimate the impact on the stock market.

Based on the Fama-French three-factor model (Fama & French, 1992), we use the historical return of stocks to estimate the expected returns, and the expected returns of stocks are calculated as shown in Eqs. (1):

Table 1. Introduction to Major Internet Media Platforms

Internet media	Type	Site Positioning	Users Covered
Phoenix	Official	China's leading news media company	374 Million
Securities Times	Official	China Securities Regulatory Commission designated disclosure platform	460 Million
Sina	Mass	Internet media platform	136 Million
Tencent	Mass	Internet media platform	493 Million
Hexun	Professional	China's earliest financial information portal	100 Million
Tonghuashun	Professional	Internet financial data service provider	48.25 Million
Eastmoney	Professional	Professional Internet financial media	62.52 Million

Figure 1. The average amount of news coverage on three media platforms



$$\left(R_{it} - R_{ft}\right) = \beta_0 + \beta_1\left(R_{mt} - R_{ft}\right) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \quad (1)$$

R_{it} is the return of stock *i* at time *t* and R_{ft} is the treasury bill rate. SMB_t is the market value factor at time *t*, which is calculated on the average return of the difference between small and big stock portfolios. HML_t is the book-to-market ratio factor at time t, and it is the difference between value and growth stock portfolios. R_{mt} represents the market return on time t and $R_{mt} - R_{ft}$ shows the market risk premiums. The data comes from China Stock Market Accounting Research (CSMAR), a database developed according to international database standards and tailored to the financial and economic characteristics of China. The AR of stock i on day t is defined as in Eqs. (2):

$$AR_{i,t} = R_{i,t}^{A} - R_{i,t}^{B} \quad (2)$$

In this formula, $t = 0$ represents the published day of news. $R_{i,t}^{A}$ is the actual return and $R_{i,t}^{B}$ is the predicted return on day t of the event period. We also calculate the cumulative abnormal return (CAR) as alternative dependent variables.

3.3 Control Variables

Other control variables are selected (as shown in Table 2), and they can be divided into three categories:

1. Website attributes of Internet media platforms. Website data mainly include website traffic Internet protocol (IP) addresses. Website traffic measures the number of unique *IP* addresses that visit a website daily. These data are obtained from Alexa, which provides website traffic queries, and rankings.
2. Fundamental factors of listed companies. We obtain the company size ($Size$), market value (MV), return on assets (ROA), the proportion of institutional investors ($Proportion$),

Table 2. Definitions of Variables

Variables Type	Variables Name	Variables Symbols	Variables Definition
Dependent Variables	Abnormal Return	AR	The difference between the actual and expected returns
	Cumulative Abnormal Return	CAR	Accumulated abnormal returns over a certain time period
Independent Variables	Official Media	Official	Percentage of official media news
	Professional Media	Pro	Percentage of professional media news
	Mass Media	Mass	Percentage of mass media news
Control Variables	IP	IP	Website visits
	Company Size	Size	Company Size
	Market Value	MV	Market Value is calculated by multiplying the share price by total share capital.
	Return on Assets	ROA	ROA is the ratio of net income after tax to total assets.
	Shareholding ratio	Proportion	Shareholding of institutional investors
	Operating Leverage	DOL	Operating leverage is the ratio of the rate of change in EBITDA to the rate of change in production and sales.
	Earnings Per Share	EPS	Earnings per share is the ratio of profit after tax to total equity.
	Analyst Attention	AnaAttention	Mentions of the stock in analyst reports
	Research attention	Report	Mentions of the stock in research reports
	News Repeat	Repeat	Number of repetitions per news article
	News Sentiment	Sentiment	Percentage of positive words
Other Variables	Return of stock *i*	R_{it}	Return of stock *i* at time *t*
	Risk-free rate of return at time *t*	R_{ft}	One-Year Treasury Bill Interest Rate
	Market return	Rm_t	CSI 300 Index Return
	Size factor	SMB_t	Different return between small and big market value portfolio
	Book-to-market factor	HML_t	Different return between high and low book-to-market value portfolio

Notes: This table introduces all the variables, including the type of variable, variable name, variable symbols, and variable definition.

firm leverage (DOL), earnings per share (EPS), analysts' attention ($AnaAttention$) and reports' attention ($Report$). The data also comes from CSMAR.

3. News dissemination attributes. We obtain the number of republished news items ($Repeat$) as the control variable. We also count the percentage of positive words as the *sentiment* of the news.

All the variables for each stock at the daily level and more details are shown in Table 2. Table 3 shows the summary statistics of all variables. The panel is unbalanced because not all stocks can obtain media coverage daily. Our observations include 2727 stocks for nearly 10,000 trading days (January 2015 to December 2018).

4. EMPIRICAL RESULTS

This section presents the main findings of this paper. In section a, we first calculate AR during the event window and obtain the regression for different media platforms. In section b, we test the four hypotheses proposed in Section 2. In section c, we use the Baidu index to alleviate endogenous problems. In section d, we discuss our findings under different conditions. Section e presents the robustness check.

4.1 Preliminary Result

First, we count AR generated by news releases from three types of media platforms during the event window. Table 4 reports the AR for three types of media platforms during the event periods. The day of the news release ($t = 0$) produces significant abnormal returns. However, official and professional media coverage generates significant positive abnormal returns, while mass media coverage generates significant negative abnormal returns. These performance differences exist for six periods in the event window, although some results lack significance. The news release generates the most significant impact on the day ($t = 0$) and the next day ($t = 1$).

To further test this difference around media platforms, we run a panel regression from each stock i on day $t's$ coverage by official media, professional media, and mass media with the next day's AR . We run the following regression described by Eqs. (3). $Official, Pro, Mass$, control variables $X_{i,t}$, and this day's AR are used as explanatory variables. α_i and μ_t represent the stock and time effects:

$$AR_{i,\ t+1} = \beta_o Official_{i.t} + \beta_p Pro_{i,t} + \beta_m Mass_{i,t} + \delta AR_t + \gamma X_{i,t} + \alpha_i + \mu_t + \epsilon_{i,t+1} \quad (3)$$

Table 5 reports the results from different media platforms in Eqs. (3). We obtain the full effect of three media platforms together in columns (1) to (3) and consider each platform in columns (4) to (6).

High official and professional media coverage can predict a positive AR , but high mass media coverage has the opposite results. This is significant at the 1% level except for some results of official media in column (4), which may be due to the low coverage of official media (see Fig. 1). We also control the stock and time effects. News sentiment and control variables are considered in column (3), and these results are also robust.

As shown in Table 5, with an increase in official media by one standard deviation on day t , the AR on the next day would increase by approximately 0.123 standard deviations. Professional media would increase the AR on day $t+1$ by approximately 0.119 standard deviations, which is less than official media. In contrast, an increase in mass media by one standard deviation on day *t* decreases the AR on day $t+1$ by approximately 0.087 standard deviations. Our findings support Hypothesis 1. This means that the type of media platform is more likely to affect the stock market. Official and professional media play the role of trust endorsement for news to capture information, while there is a relatively low authority in the mass media, and abnormal returns have progressively decreased.

4.2 Potential Mechanisms

This section conducts a series of tests to discuss the potential mechanisms between media platforms and stock performance which discuss in Section 2. First, we examine whether the impact of media

Table 3. Descriptive statistics of the main variables

Panel A: Quantities of all news	
All news count	56,095
Official Media	4,176
Professional media	30,759
Mass media	21,160

Panel B: Descriptive statistics for news of three media platforms					
Media platforms	**Mean**	**SD**	**Min**	**Median**	**Max**
Official	0.032	0.172	0	0	1
Pro	0.684	0.450	0	1	1
Mass	0.283	0.435	0	0	1

Panel C: Descriptive statistics for official media					
Official media	**Mean**	**SD**	**Min**	**Median**	**Max**
AR	0.028	1.322	-4.214	-0.036	6.834
Size	0.214	2.279	-0.113	-0.107	31.040
MV	0.055	1.385	-0.370	-0.242	18.110
IP	0.019	0.128	-0.029	-0.027	0.602
ROA	-0.076	0.776	-6.614	0.026	0.640
Proportion	-0.060	1.029	-1.585	-0.132	2.446
DOL	0.015	0.400	-0.782	-0.045	8.673
EPS	-0.132	0.388	-3.792	-0.141	2.820
AnaAttention	-0.301	0.678	-0.920	-0.504	2.995
Report	-0.287	0.671	-0.826	-0.536	3.870
Repeat	2.659	7.590	1.000	1.000	70.000
Sentiment	-0.150	0.939	-4.177	-0.084	1.012

Panel D: Descriptive statistics for professional media					
Professional media	**Mean**	**SD**	**Min**	**Median**	**Max**
AR	-0.034	1.044	-5.887	-0.100	7.656
Size	-0.048	0.681	-0.114	-0.106	38.48
MV	-0.023	0.836	-0.379	-0.216	26.58
IP	0.038	0.067	-0.0240	0.010	0.316
ROA	0.030	0.536	-54.13	0.037	13.57
Proportion	-0.061	1.017	-1.585	-0.030	2.701
DOL	-0.001	1.262	-9.543	-0.048	142.3
EPS	-0.038	0.738	-4.770	-0.119	19.66
AnaAttention	-0.135	0.874	-0.920	-0.420	4.494
Report	-0.142	0.864	-0.826	-0.472	6.893
Repeat	11.120	26.660	1.000	1.000	224.000
Sentiment	-0.021	1.241	-4.177	0.363	1.012

continued on following page

Table 3. Continued

Panel E: Descriptive statistics for mass media					
Mass media	Mean	SD	Min	Median	Max
AR	0.038	1.145	-5.491	-0.067	6.811
Size	0.042	1.340	-0.114	-0.107	32.620
MV	0.050	1.273	-0.373	-0.245	25.530
IP	0.447	1.926	-0.024	-0.011	10.320
ROA	-0.024	1.469	-54.130	0.034	0.851
Proportion	-0.002	1.084	-1.585	0.005	2.594
DOL	-0.014	0.440	-28.380	-0.047	6.638
EPS	-0.066	0.517	-4.770	-0.127	13.870
AnaAttention	-0.098	0.932	-0.920	-0.420	5.244
Report	-0.093	0.948	-0.826	-0.472	7.279
Repeat	1.527	7.114	1.000	1.000	160.000
Sentiment	-0.233	0.831	-4.177	-0.141	1.012

Notes: The data are from the news of seven media platforms and CSMAR. This table presents the descriptive statistics for the variables. Panels A to D show the statistics of the three media platforms from a holistic and separate perspective. Panel A presents the summary of all media platforms. Panel B summarizes the variables of official media. Panel C shows the statistics of professional media, and panel D is the summary of mass media.

Table 4. AR of three media platforms

Event windows	Official media (%)	Professional media (%)	Mass media (%)
-10	-0.122	0.034	0.022
-9	-0.213	0.065	0.004
-8	-0.290	0.075	0.006
-7	-0.047	0.085*	-0.054*
-6	0.117	0.140*	-0.070
-5	0.190	0.182	-0.114
-4	0.250	0.272	-0.152
-3	0.507	0.424*	-0.083
-2	0.825	0.660	-0.012*
-1	1.195*	1.010*	-0.041*
0	1.386**	1.021***	-0.194***
1	1.290**	0.920***	-0.221**
2	1.227*	0.854**	-0.366
3	1.101	0.777	-0.567
4	1.070	0.707*	-0.495
5	0.984*	0.628	-0.428
6	0.911	0.597	-0.628*
7	0.997	0.569	0.071
8	0.986	0.504	0.060
9	0.848	0.465	0.145
10	0.871	0.433	0.244

Note: This table reports the abnormal returns generated by news exposure on three media platforms. All values are expressed as percentages.

Table 5. AR with panel regressions

Variables	(1) AR(+1)	(2) AR(+1)	(3) AR(+1)	(4) AR(+1)	(5) AR(+1)	(6) AR(+1)
AR	0.110*** (15.79)	0.107*** (14.12)	0.112*** (15.83)	0.108*** (14.03)	0.108*** (14.07)	0.108*** (14.09)
Official	0.130*** (2.61)	0.102* (1.72)	0.123** (2.35)	0.007 (0.11)		
Pro	0.116*** (5.85)	0.104*** (4.59)	0.119*** (5.90)		0.103*** (4.60)	
Mass	-0.096*** (-3.16)	-0.077*** (-2.61)	-0.087*** (-2.82)			-0.108*** (-4.73)
Size		-0.005 (-0.09)	0.004 (0.27)	0.043 (0.31)	-0.011 (-0.20)	-0.007 (-0.13)
MV		0.032 (1.22)	0.007 (0.42)	0.005 (0.36)	0.031 (1.19)	0.031 (1.16)
IP		-0.003 (-0.41)	-0.016** (-2.23)	-0.023*** (-3.33)	-0.013 (-0.95)	-0.013 (-0.97)
ROA		-0.015 (-1.09)	0.027*** (2.70)	0.012 (1.40)	0.017* (1.78)	0.017* (1.77)
Proportion		0.017* (1.80)	0.013 (1.51)	0.027*** (2.68)	-0.013 (-0.97)	-0.133 (-0.97)
DOL		0.035*** (4.25)	0.032*** (4.85)	0.032*** (4.83)	0.036*** (4.39)	0.036*** (4.38)
EPS		-0.022 (-1.06)	-0.012 (-0.67)	-0.012 (-0.67)	-0.019 (-0.90)	-0.019 (-0.90)
AnaAttention		-0.019 (-0.49)	-0.066** (-1.98)	-0.407 (-1.23)	-0.022 (-0.57)	-0.021 (-0.53)
Report		0.063* (1.65)	0.086*** (2.62)	0.071** (2.19)	0.066* (1.72)	0.065* (1.70)
Repeat		0.011 (1.07)	0.014 (1.46)	0.014 (1.40)	0.008 (0.82)	0.009 (0.82)
Sentiment			0.046*** (6.18)	0.048*** (6.43)	0.030*** (3.46)	0.030*** (3.44)
N	23,561	23,561	19,648	19,648	19,648	19,648
Number of Stocks	2,727	2,727	2,695	2,695	2,695	2,695
Stock FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
R-squared	0.023	0.017	0.086	0.083	0.074	0.075

z-statistics in parentheses. Standard errors clustered by stocks.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table reports panel regression results with AR(+1) as the dependent variable. All regressions include time fixed effects and stock effects clustered by stocks.

platforms on stock performance is related to their news content. Second, we test whether the impact of media platforms on stock performance varies with audiences. Finally, we analyze the timeliness of news.

4.2.1 Content of Platforms

We measure the news content in three dimensions: news keywords, reported stocks, and news sentiment. We mainly use keyword statistics to measure news content. If the news content is more differentiated for platforms, their keywords will also be more dissimilar. If the news content for platforms converges, the content and distribution of their keywords will also be roughly in agreement. We select the top 50 keywords for each media platform and find that news content for the three types of media platforms does not differ substantially in terms of either keyword distribution or content (see Table 14 in the Appendix). All three types of media platforms focus more on covering corporate governance news, followed by public news and, finally, stock news. In terms of keyword content, most of the keywords are consistent, with only a few differences in the formulation of keywords. We illustrate the top ten stocks with the most media coverage in each category and find that seven of the top ten stocks are covered by three types of media platforms, which is consistent with the overall distribution (see Table 15 in the Appendix). In addition, sentiment is a meaningful way to measure news content. We count the average sentiment of three types of media platforms. The sentiment of official media news is 0.76, that of professional media news is 0.81, and that of mass media news is 0.75. The overall sentiment tends to be positive, and the positive sentiment is higher for professional media and more divergent for mass media.

We screen the news of the same events, and samples are reported by at least two or more types of media platforms. Table 6 shows the results, and the regressions for the same news covered by at least two kinds of media platforms are still robust. Columns (4) to (5) of Table 6 report the results for the sentiment. The influence of media platforms tends to be more pronounced in weaker sentiment, and stronger sentiment tends to cause investors to behave irrationally or even trigger herding effects. At this point, the influence of the media platform is still present but with a reduced coefficient. In summary, after considering keywords, stocks, and sentiment, we verify that the impact of media platforms on stock performance is not related to their news content. Therefore, hypothesis H2(b) is confirmed.

Table 6. Panel regressions of news content and sentiment

Variables	News Content			News Sentiment	
	(1) AR(+1)	(2) AR(+1)	(3) AR(+1)	(4) AR(+1)	(5) AR(+1)
AR	0.147*** (8.60)	0.145*** (10.24)	0.117*** (9.37)	0.124*** (6.09)	0.064*** (4.31)
Official	0.219** (2.21)	0.154* (1.72)	0.091 (0.70)	0.325** (2.22)	-0.703 (-0.57)
Pro	0.288*** (2.70)	0.243*** (2.75)	0.126*** (2.79)	0.276*** (4.99)	0.008** (2.19)
Mass	-0.208** (-2.16)	-0.117 (-1.41)	-0.123*** (-2.74)	-0.912* (-1.73)	-0.071* (-1.81)
N	2,873	4,458	5,130	9821	9827
Number of Stocks	1,233	1,490	1,776	2,638	1,948
Stock FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Stock Controls	YES	YES	YES	YES	YES
Sentiment	YES	YES	YES	YES	YES
R-squared	0.051	0.050	0.038	0.086	0.094

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results of news content and sentiment with AR (+1) as the dependent variable. We verify the impact of platforms in two dimensions: news content and news sentiment. First, we count stocks that are covered by at least two types of media platforms with the same news and regress them with Eqs (3). Column (1) is the result of being covered by at least the official media and other media with common news. Column (2) is the result of the common news coverage by at least professional media and other media. Column (3) is the result of at least being covered by mass media and other media with common news. Second, we sort the news sentiments and divide them into two categories. Column (4) is the samples with weaker sentiments, and column (5) is the samples with stronger sentiments. All regressions include time fixed effects and stock effects clustered by stocks.

4.2.2 Audiences of Platforms

In this section, we conduct several analyses to assess whether the impact of media platforms on stock performance varies with audiences. As specifically discussed previously, the audience of the stock market can mainly be divided into institutional investors and retail investors.

In the first regression of Table 7, we test whether institutional investors are more likely to devote their attention to professional media and whether retail investors are more inclined to mass media, as mentioned in hypothesis 3. We obtain each stock's proportion of institutional investors (INS) on day t, and we divide the samples into two groups based on INS.

Table 7 reports the results based on the effect of institutional investors. In Table 7, column (1) of *Low-INS*, the coverage on day *t* from mass media is significantly negative. In column (2) of *High-INS*, the coverage on day *t* from professional media is significantly positive. This means that retail investors may rely on mass media coverage for information. Mass media have a larger audience, so once the coverage is published on mass media, the coverage would provide the most publicly available information, and the AR of the stock would decrease. In contrast, institutional investors obtain their information primarily from professional media. They have a stronger ability to interpret the information so that institutional investors can obtain AR from the stock market.

Table 7. AR with panel regressions

Variables	(1) AR(+1) Low-INS	(2) AR(+1) High-INS	(3) AR(+1)	(4) AR(+1)
AR	0.087*** (8.04)	0.095*** (8.52)	0.111*** (15.93)	0.112*** (15.95)
Official_Media	-0.004 (-0.04)	0.105 (1.15)	0.120** (2.41)	0.118** (2.25)
Pro_Media	0.008 (0.23)	0.150*** (4.73)	0.106*** (5.41)	0.111*** (5.55)
Mass_Media	-0.104* (-1.70)	-0.012 (-0.21)	-0.072*** (-2.66)	-0.072** (-2.55)
Official*INS			-0.001 (-0.68)	-0.001 (-0.72)
Pro*INS			0.001* (1.79)	0.001** (1.98)
Mass*INS			-0.001* (-1.90)	-0.001* (-1.67)
N	9,811	9,837	23,561	19,648
Number of Stock	1,817	1,616	2,727	2,695
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Stock Controls	YES	YES	NO	YES
Sentiments	YES	YES	NO	YES
R-squared	0.068	0.015	0.024	0.030

z-statistics in parentheses. Standard errors clustered by stocks.
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results with AR (+1) as the dependent variable. All regressions include time fixed effects and stock effects clustered by stocks. Column (1) is the group of low institutional investor shareholdings, and column (2) is the group of high institutional investor shareholdings. Columns (3) to (4) show the interaction of media platforms and institutional investors' shareholdings.

To further test how institutional investors predict a higher AR , we add the proxy of institutional investors and media platforms to test the moderating effect under different media platforms. In Table 7, column (4), $Pro * INS$ is significantly positive, and $Mass * INS$ is significantly negative. The increase in institutional investors predicts a higher AR on the next day for professional media while predicting an opposite AR on the next day for mass media. This evidence suggests that institutional investors' attention can enhance the positive effect of professional media and the negative impact of mass media. As such, H3 is accepted.

4.2.3 Timeliness of Platforms

In this section, we examine whether the impact of media platforms on stock performance is related to the release time of their news. We count the time difference between repeat releases (see Table 16 in the Appendix). Approximately 69.32% of the repeated news is published on the same day, and 76.75% is published within 1 day. Repeat news published within three days accounts for approximately 77.86% of all repeated news. A good explanation might be that Internet media platforms could quickly respond to news, and the time difference between news on media platforms is significantly reduced.

To further verify our hypothesis, we keep the news published within 0, 1, 2 days, and more than 3 days. The regression results are shown in Table 8. The influence of media platforms remains regardless of the time interval between news releases. This suggests that the impact of media platforms on stock performance is not related to the release time of their news. These findings support H4(b).

Table 8. Panel regressions of release time

Variables	(1) <1 day AR(+1)	(2) < 2 days AR(+1)	(3) < 3 days AR(+1)	(4) > = 3 days AR(+1)
AR	0.082*** (5.94)	0.081*** (5.92)	0.079*** (5.84)	-0.039 (-1.14)
Official	0.248* (1.79)	0.200* (1.76)	0.154 (1.08)	0.108 (0.42)
Pro	0.171*** (2.64)	0.176*** (2.90)	0.136** (2.26)	0.327** (2.00)
Mass	-0.137** (-2.15)	-0.152** (-2.31)	-0.114* (-1.76)	-0.529*** (-2.99)
N	4,774	4,871	4,891	747
Number of Stocks	863	888	894	338
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Stock Controls	YES	YES	YES	YES
Sentiment	YES	YES	YES	YES
R-squared	0.013	0.019	0.011	0.035

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results of release time with AR (+1) as the dependent variable. We count the release time of all the same news. The first to fourth columns are the samples of news published within 0, 1, 2 days, and more than 3 days. All regressions include time fixed effects and stock effects clustered by stocks. Column (1) is samples of identical news published on the same day, and column (2) is samples published within one day. Column (3) shows samples published within two days. Column (4) is samples published three days or more.

4.3 Endogeneity Problems

In the previous analysis, AR on day *t+1* is used to reduce the interference of reverse causality. There may still be some endogeneity problems. Media coverage may focus more attention on stocks with more extreme abnormal returns. Therefore, we further use instrumental variables to alleviate the impact of endogeneity problems. We use interactive items based on the Baidu index and the average abnormal return of each stock. Similar to the Google index, the Baidu index is a search index of the weighted sum of the search frequency of each keyword in the Baidu web search. Baidu is the largest search engine in the Chinese market, and many users reach relevant pages through Baidu. We collect each platform's name and shorter form from January 1, 2015, to December 31, 2018 (as shown in Table 9). Thus, we obtain the proportion of the Baidu index of each media platform.

Instrumental variables must be selected to satisfy their correlation with endogenous explanatory variables. On the one hand, investors obtain news content through Baidu search links to relevant websites, so news reports are related to investors' searches. On the other hand, the Baidu index of the website itself has difficulty affecting the abnormal return. AR is a variable that changes with the individual, and the Baidu index is unrelated to individual stocks. Therefore, it may lead to the failure of instrumental variables. Here, we obtain the average abnormal return of each stock and multiply it by the Baidu index of each media platform to ensure effectiveness.

The estimation results of the instrumental variables are shown in Table 10. Columns (1) to (3) are the estimation results of the first phase. The Baidu index of each media platform shows significant correlations with media coverage. The Baidu index of mass media has negative correlations with media coverage, which means that retail investors' search behavior declines when they face more news coverage. The Lagrange multiplier (LM) statistic under the identification test is 19.260, significantly rejecting the unrecognizable original hypothesis. The F value is 8.710, which can reject weak instrumental variables. Two-stage least squares ($2SLS$) in column (4) show that after controlling for endogeneity, the results remain solid. High coverage of $Official$ and Pro media also predicts positive AR , and increased coverage of $Mass$ media predicts negative AR .

4.4 Trait Analysis

Since market cycles have a huge impact on asset returns, it is possible that investor behavior and information flows may also change during bear and bull cycles. Therefore, we regress our model on bear and bull markets to further test this effect in different cycles. For the bear and bull market division, we follow a previous study (Yu et al., 2017) and use the Shanghai Stock Exchange Index for 2015 to 2018 as the target index. We also use Hodrick–Prescott (HP) filtering to decompose trends and obtain 2 trough points and 1 crest point (Table 11). The three points jointly determine the bull and bear stages and meet the requirements of more than 25% return changes and fluctuations lasting

Table 9. Keywords of each media platform in the Baidu Index

Media Platforms	Type	Keywords
Phoenix	Official	phoenix, phoenix website
Securities Times	Official	securities times, securities, securities times website
Sina	Mass	sina, sina website, sina finance
Tencent	Mass	tencent, tencent website, tencent finance
Hexun	Professional	hexun, hexun website
Tonghuashun	Professional	tonghuashun, tonghua
Eastmoney	Professional	eastmoney, eastmoney website

Table 10. 2SLS of instrumental variables

Variables	(1) Official	(2) Pro	(3) Mass	(4) 2SLS AR(+1)
Official_baidu	0.043 (0.79)			
Pro_baidu		0.076** (2.27)		
Mass_baidu			-0.026*** (-3.45)	
Official				4.473** (2.37)
Pro				2.839*** (5.80)
Mass				-2.089*** (-3.81)
N	15,633	15,633	15,633	19,648
Number of Stocks	2,677	2,677	2,677	2,695
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Stock Controls	YES	YES	YES	YES
Sentiment	YES	YES	YES	YES
R-squared	0.004	0.057	0.058	0.055
KP-LM: 19.260 F:8.710				

z-statistics in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Notes: This table reports panel regression results of instrumental variables by using two-stage least squares (2SLS). All regressions include time fixed effects and stock effects clustered by stocks.

Table 11. Bear and bull market division results

Date	Return_Change	Duration	Bear/Bull Market
1.1.2015-6.11.2015	151%	191 days	Bull
6.12.2015-2.29.2016	-48%	263 days	Bear

Notes: This table reports the division results of the bear and bull markets. We use the Shanghai Stock Exchange closing index to determine the fluctuation point. In addition, we also employ Hodrick–Prescott (HP) filtering to decompose trends. Return_Change is the range return of this period, and Duration denotes the total days of return changes by more than 25%.

for more than six months. We separately examine the effects of media platforms in bear and bull markets. The regression results are shown in Table 12.

The results show that three media platforms significantly impact AR in a bear market but have mostly insignificant effects in a bull market. This may be due to the influx of irrational individual investors during bull markets and the lack of attention to media information. These speculators leave the stock market during a bear market therefore more influence from the media platforms could be observed.

Table 12. AR in bear and bull markets

Variables	(1) Bear AR(+1)	(2) Bull AR(+1)
AR	0.059* (1.92)	0.138 (1.58)
Official	0.539* (1.67)	0.084 (0.19)
Pro	0.275** (2.20)	0.170 (0.40)
Mass	-0.188* (-1.74)	-0.272 (-0.81)
N	3,315	803
Number of Stocks	1,369	556
Stock FE	YES	YES
Time FE	YES	YES
Stock Controls	YES	YES
Sentiments	YES	YES
R-squared	0.015	0.067

Robust t-statistics in parentheses. Standard errors clustered by stocks.
*** p<0.01, ** p<0.05, * p<0.1
Notes: This table reports panel regression results of bear and bull markets with AR(+1) as the dependent variable but with an unbalanced panel. All regressions include time fixed effects and stock effects clustered by stocks. Column (1) is the panel regression on a bear market, and Column (2) is on a bull market.

4.5 Robustness Checks

In the robustness tests, we replace the dependent variable with CAR , and the results remain consistent with the primary regression (see Table 13 for details). To avoid the effect of repeated information, we delete the repeated news and only keep the exclusive news in the regression (see Table 17 in the Appendix). We also use dummy variables to measure media platforms, and the results are similar to those of the baseline model (see Table 18 in the Appendix).

5. CONCLUSION

This study provides evidence that media platforms, as the distribution vehicle and trust endorsements for news, are themselves influential to the stock market. Using news data from Chinese Internet media platforms from 2015 to 2018, this paper confirms the hypothesis that media platforms impact stock performance, which varies with the type of platform. According to their authority or endorsement, media platforms are categorized as official, professional, and mass media platforms. We find that high official and professional media coverage predict positive abnormal returns, while high mass media coverage predicts the opposite. To understand the underlying mechanisms, we investigate the impact of media platforms on stock performance from the perspectives of platform content, audience, and release time. The investor-driven audience has a moderating effect on the influence of media platforms, and there is limited evidence for the role of content and timeliness in the Internet environment. This research innovatively suggests how the media can influence stock performance from a platform perspective, providing a necessary complement to traditional news-aware stock movements.

Table 13. CAR with panel regressions

Variables	(1)	(2)	(3)	(4)
	CAR(0,1)	CAR(0,3)	CAR(0,5)	CAR(0,10)
Official	0.114**	0.114**	0.120**	0.150**
	(2.32)	(2.16)	(2.16)	(2.39)
Pro	0.077***	0.082***	0.085***	0.106***
	(4.55)	(4.47)	(4.40)	(4.90)
Mass	-0.024	-0.004	-0.098**	-0.006**
	(-1.01)	(-1.27)	(-2.16)	(-2.45)
N	19,648	19,648	19,648	19,648
Number of Stocks	2,695	2,695	2,695	2,695
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Stock Controls	YES	YES	YES	YES
Sentiment	YES	YES	YES	YES
R-squared	0.004	0.004	0.004	0.004

z-statistics in parentheses. Standard errors clustered by stocks.

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results with CAR as the dependent variable but with an unbalanced panel. All regressions include time fixed effects and stock effects clustered by stocks.

This paper addresses several hypotheses about the impact of media platforms on the stock market in terms of news content, platform audience, and the release time of the news. Our conclusions still hold after mitigating endogeneity and multiple robustness tests. However, these hypotheses are verified by the data released between 2015 and 2018 in Chinese markets. It would be of great interest to expand this analysis to other financial markets and other periods, especially to developed countries in recent years, to determine whether this effect is still present. In addition, we would like to explore alternative mechanisms for the impact of media platforms on stock markets, including investor sentiment and corporate or media reputation. In the near future, supported by more sufficient data, it would be valuable to disentangle these mechanisms.

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REFERENCES

Badham, M., & Mykkänen, M. (2022). A Relational Approach to How Media Engage With Their Audiences in Social Media. *Media and Communication*, *10*(1), 54–65. doi:10.17645/mac.v10i1.4409

Basak, S., & Pavlova, A. (2013). Asset Prices and Institutional Investors. *The American Economic Review*, *103*(5), 1728–1758. doi:10.1257/aer.103.5.1728

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, *27*, 1–36. doi:10.2307/2491062

Boehmer, E., Masumeci, J., & Poulsen, A. B. (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics*, *30*(2), 253–272. doi:10.1016/0304-405X(91)90032-F

Bruns, A. (2012). Reconciling Community and Commerce? *Information Communication and Society*, *15*(6), 815–835. doi:10.1080/1369118X.2012.680482

Bucher, T. (2020). The right-time web: Theorizing the kairologic of algorithmic media. *New Media & Society*, *22*(9), 1699–1714. doi:10.1177/1461444820913560

Calomiris, C. W., & Mamaysky, H. (2019). How news and its context drive risk and returns around the world. *Journal of Financial Economics*, *133*(2), 299–336. doi:10.1016/j.jfineco.2018.11.009

Chan, W. S. (2003). Stock price reaction to news and no-news: Drift and reversal after headlines. *Journal of Financial Economics*, *70*(2), 223–260. doi:10.1016/S0304-405X(03)00146-6

Chen, Y., Hu, C., Zhang, W., & Li, Q. (2021). CEO Exposure, Media Influence, and Stock Returns. *Journal of Global Information Management*, *29*(6), 1–19. doi:10.4018/JGIM.20211101.oa43

Courtney, C., Dutta, S., & Li, Y. (2017). Resolving Information Asymmetry: Signaling, Endorsement, and Crowdfunding Success. *Entrepreneurship Theory and Practice*, *41*(2), 265–290. doi:10.1111/etap.12267

Cowan, A. R. (1992). Nonparametric event study tests. *Review of Quantitative Finance and Accounting*, *2*(4), 343–358. doi:10.1007/BF00939016

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1988). *What moves stock prices?* National Bureau of Economic Research Cambridge. doi:10.3386/w2538

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*(4), 703–738. doi:10.1086/261703

Dessein, W. (2002). Authority and Communication in Organizations. *The Review of Economic Studies*, *69*(4), 811–838. doi:10.1111/1467-937X.00227

Donsbach, W. (2004). Psychology of News Decisions: Factors behind Journalists' Professional Behavior. *Journalism*, *5*(2), 131–157. doi:10.1177/146488490452002

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465. doi:10.1111/j.1540-6261.1992.tb04398.x

Fang, L., & Peress, J. (2009). Media Coverage and the Cross-section of Stock Returns. *The Journal of Finance*, *64*(5), 2023–2052. doi:10.1111/j.1540-6261.2009.01493.x

Fletcher, R., & Park, S. (2017). The Impact of Trust in the News Media on Online News Consumption and Participation. *Digital Journalism*, *5*(10), 1281–1299. doi:10.1080/21670811.2017.1279979

Garz, M. (2014). Good news and bad news: Evidence of media bias in unemployment reports. *Public Choice*, *161*(3), 499–515. doi:10.1007/s11127-014-0182-2

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the Stock Market. *The Journal of Finance*, *63*(6), 2557–2600. doi:10.1111/j.1540-6261.2008.01408.x

Gunther, A. C., Christen, C. T., Liebhart, J. L., & Chih-Yun Chia, S. (2001). Congenial Public, Contrary Press, and Biased Estimates of the Climate of Opinion. *Public Opinion Quarterly*, *65*(3), 295–320. doi:10.1086/322846 PMID:11600967

Huang, A. G., Tan, H., & Wermers, R. (2020). Institutional Trading around Corporate News: Evidence from Textual Analysis. *Review of Financial Studies*, *33*(10), 4627–4675. doi:10.1093/rfs/hhz136

Jacobs, A. M., Matthews, J. S., Hicks, T., & Merkley, E. (2021). Whose News? Class-Biased Economic Reporting in the United States. *The American Political Science Review*, *115*(3), 1016–1033. doi:10.1017/S0003055421000137

Kahneman, D. (1973). *Attention and effort* (Vol. 1063). Citeseer.

Kim, S. J. (2016). A repertoire approach to cross-platform media use behavior. *New Media & Society*, *18*(3), 353–372. doi:10.1177/1461444814543162

Knittel, C. R., & Stango, V. (2014). Celebrity Endorsements, Firm Value, and Reputation Risk: Evidence from the Tiger Woods Scandal. *Management Science*, *60*(1), 21–37. doi:10.1287/mnsc.2013.1749

Kohlhas, A. N., & Walther, A. (2021). Asymmetric Attention. *The American Economic Review*, *111*(9), 2879–2925. doi:10.1257/aer.20191432

Kumar, A., & Lee, C. M. (2006). Retail Investor Sentiment and Return Comovements. *The Journal of Finance*, *61*(5), 2451–2486. doi:10.1111/j.1540-6261.2006.01063.x

Lee, E.-J., & Tandoc, E. C. Jr. (2017). When News Meets the Audience: How Audience Feedback Online Affects News Production and Consumption. *Human Communication Research*, *43*(4), 436–449. doi:10.1111/hcre.12123

Li, Q., Chen, Y., Wang, J., Chen, Y., & Chen, H. (2017). Web media and stock markets: A survey and future directions from a big data perspective. *IEEE Transactions on Knowledge and Data Engineering*, *30*(2), 381–399. doi:10.1109/TKDE.2017.2763144

Neupane, S., & Poshakwale, S. S. (2012). Transparency in IPO mechanism: Retail investors' participation, IPO pricing and returns. *Journal of Banking & Finance*, *36*(7), 2064–2076. doi:10.1016/j.jbankfin.2012.03.010

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563–602. doi:10.1016/j.jfineco.2005.05.003

Pevzner, M., Xie, F., & Xin, X. (2015). When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. *Journal of Financial Economics*, *117*(1), 190–223. doi:10.1016/j.jfineco.2013.08.004

Price, V., Cappella, J. N., & Nir, L. (2002). Does Disagreement Contribute to More Deliberative Opinion? *Political Communication*, *19*(1), 95–112. doi:10.1080/105846002317246506

Rivera-Trigueros, I., & Olvera-Lobo, M.-D. (2021). Internet Presence and Multilingual Dissemination in Corporate Websites: A Portrait of Spanish Healthcare SMEs. *Journal of Global Information Management*, *29*(6), 1–17. doi:10.4018/JGIM.20211101.oa24

Rouibah, K., Qurban, H., & Al-Qirim, N. (2022). Impact of Risk Perceptions and User Trust on Intention to Re-Use E-Government: A Mixed Method Research. *Journal of Global Information Management*, *30*(1), 1–29. doi:10.4018/JGIM.307117

Shang, S. S. C., Wu, Y.-L., & Li, E. Y. (2017). Field effects of social media platforms on information-sharing continuance: Do reach and richness matter? *Information & Management*, *54*(2), 241–255. doi:10.1016/j.im.2016.06.008

Shin, D. (2021). A Cross-National Study on the Perception of Algorithm News in the East and the West. *Journal of Global Information Management*, *29*(2), 77–101. doi:10.4018/JGIM.2021030105

Sigelman, L. (1973). Reporting the News: An Organizational Analysis. *American Journal of Sociology*, *79*(1), 132–151. doi:10.1086/225511

Sohaib, O. (2021). Social Networking Services and Social Trust in Social Commerce: A PLS-SEM Approach. *Journal of Global Information Management*, *29*(2), 23–44. doi:10.4018/JGIM.2021030102

Sperber, D. (2010). The Guru Effect. *Review of Philosophy and Psychology*, *1*(4), 583–592. doi:10.1007/s13164-010-0025-0

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139–1168. doi:10.1111/j.1540-6261.2007.01232.x

Tetlock, P. C. (2011). All the News That's Fit to Reprint: Do Investors React to Stale Information? *Review of Financial Studies*, *24*(5), 1481–1512. doi:10.1093/rfs/hhq141

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, *63*(3), 1437–1467. doi:10.1111/j.1540-6261.2008.01362.x

Wang, X. W., Riaz, M., Haider, S., Alam, K. M., Sherani, , & Yang, M. (2021). Information Sharing on Social Media by Multicultural Individuals: Experiential, Motivational, and Network Factors. *Journal of Global Information Management*, *29*(6), 1–25. doi:10.4018/JGIM.20211101.oa22

Whitney, D. C., & Becker, L. B. (1982). 'Keeping the Gates' for Gatekeepers: The Effects of Wire News. *The Journalism Quarterly*, *59*(1), 60–65. doi:10.1177/107769908205900109

Xing, Y., Wang, X., Wang, F.-K., Shi, Y., He, W., & Chang, H. (2021). Ranking Influential Nodes of Fake News Spreading on Mobile Social Networks. *Journal of Global Information Management*, *29*(4), 93–130. doi:10.4018/JGIM.20210701.oa5

Yu, X., Chen, Z., Xu, W., & Fu, J. (2017). Forecasting Bull and Bear Markets: Evidence from China. *Emerging Markets Finance & Trade*, *53*(8), 1720–1733. doi:10.1080/1540496X.2016.1184141

Zhu, Y., & Dukes, A. (2015). Selective Reporting of Factual Content by Commercial Media. *JMR, Journal of Marketing Research*, *52*(1), 56–76. doi:10.1509/jmr.12.0379

APPENDIX

Table 14. Keyword Statistics for Media Platforms. This table shows the top 50 keywords for each type of media platform. We have sorted the keywords by the category of news. The category of news contains public news, stock news, and corporate governance news.

Platforms Type	News Type	Keywords	Words Count
Official media	Public News	market, technology, our government, development, growth, industry, services, future, risk, strategy, Beijing, economy, bank, internet, energy	15
	Stock News	funds, capital, quotes, trend, investment, assets, trading, hold, dividend, long position, individual stocks, investors, stock price, suspension	14
	Corporate Governance News	company, announcement, shareholders, equity, net profit, business, project, performance, disclosure, acquisition, board of directors, product, revenue, operation, research, management, subsidiary, operating, production, restructuring, reduction	21
Professional media	Public News	market, development, growth, industry, technology, service, future, industry, field, risk, platform, strategy, bank, economy, country, internet, resource	17
	Stock News	investment, capital, trading, issue, buy, hold, price, institution, sell, stock price, individual stock, suspension, subscription, cost	14
	Corporate Governance News	company, financing, financing securities, shareholders, business, cooperation, project, business, product, disclosure, performance, management, revenue, R&D, board of directors, subsidiary, restructuring, reduction, earnings	19
Mass media	Public News	regulation, risk, technology, CSRC, bank, plan, Beijing, construction, Internet, control, industry, technology, implementation, Shenzhen Stock Exchange, service	15
	Stock News	investment, funds, assets, funds, price, holdings, institutions, trading, investors, returns, individual stock	11
	Corporate Governance News	announcement, shareholders, board of directors, proposal, disclosure, vote, raise, equity, business, operation, subsidiary, performance, net profit, product, guarantee, acquisition, transfer, revenue, resolution, articles of association, asset reorganization, repurchase, financing, reduction of holdings	24

Table 15. TOP 10 stocks for Media Platforms. We count the amount of news for each stock in each type of media and rank. Table 6 shows the top 10 stocks with the most coverage on each type of media platform.

Official media	Professional media	Mass media
000333.SZ	600519.SH	603288.SH
000725.SZ	002024.SZ	000333.SZ
002549.SZ	000333.SZ	000725.SZ
002044.SZ	002285.SZ	002450.SZ
000338.SZ	002549.SZ	000338.SZ
002024.SZ	000725.SZ	002044.SZ
002680.SZ	603288.SH	002680.SZ
002450.SZ	600559.SH	002024.SZ
603288.SH	002450.SZ	600519.SH
002143.SZ	600559.SH	002549.SZ

Table 16. Same news release interval. We filter 6460 groups of duplicate news by the cosine similarity of keywords. Firstly, we use the keywords of each news article in section (i) and calculate the cosine similarity between the news articles. Secondly, we count the number of repetitions in each news and keep the news with repetitions greater than 0. Then, we summarized the earliest and latest time interval between the repeat news articles.

Time interval	News quantity	Percentage
< 1 day	4478	69.32%
< 2 days	4958	76.75%
< 3 days	5030	77.86%
> = 3 days	1430	22.14%

Table 17. AR with a Panel Regression Only Considering Exclusive News

Variables	(1) AR(+1)	(2) AR(+1)	(3) AR(+1)	(4) AR(+1)	(5) AR(+1)	(6) AR(+1)
AR_mean_std	0.127***	0.126***	0.126***	0.125***	0.127***	0.127***
	(8.09)	(8.08)	(7.93)	(7.85)	(7.54)	(7.56)
Official	0.122*	0.120*	0.123*	0.030		
	(1.78)	(1.74)	(1.66)	(0.42)		
Pro	0.144***	0.145***	0.161***		0.135***	
	(5.31)	(5.34)	(5.90)		(4.27)	
Mass	-0.147*	-0.127***	-0.116***			-0.137***
	(-1.82)	(-3.08)	(-2.82)			(-4.35)
N	13,775	13,775	13,447	13,447	13,447	13,447
Number of Stocks	2,636	2,636	2,603	2,603	2,603	2,603
Stock FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Stock Controls	NO	YES	YES	YES	YES	YES
Sentiments	NO	NO	YES	YES	YES	YES
R	0.020	0.021	0.024	0.023	0.025	0.025

Robust z-statistics in parentheses. Standard errors clustered by stocks.

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results with AR(+1) as the dependent variable but with an unbalanced panel. AR(+1) means the abnormal return for the day after the news release. AR indicates the abnormal return on the day of the news release. This table reports panel regression results with AR(+1) as the dependent variable. All regressions include time-fixed effects and stock effects clustered by stocks.

Table 18. Media flatforms by dummy variables with Panel Regressions

Variables	(1) AR(+1)	(2) AR(+1)	(3) AR(+1)	(4) AR(+1)	(5) AR(+1)	(6) AR(+1)
AR	0.110*** (15.78)	0.110*** (15.82)	0.112*** (15.83)	0.092*** (13.32)	0.108*** (14.08)	0.112*** (15.83)
Official_dummy	0.117** (2.43)	0.110** (2.28)	0.102** (2.28)	0.017 (0.37)		
Per_dummy	0.106*** (5.58)	0.099*** (5.13)	0.102*** (5.13)		0.088*** (4.09)	
Mass_dummy	-0.089*** (-2.97)	-0.084*** (-2.74)	-0.074** (-2.40)			-0.090*** (-4.11)
N	23,561	23,561	23,561	19,648	19,648	19,648
Number of Stocks	2,727	2,727	2,727	2,695	2,695	2,695
Stock FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Stock Controls	NO	YES	YES	YES	YES	YES
Sentiment	NO	NO	YES	YES	YES	YES
R-squared	0.025	0.025	0.032	0.063	0.018	0.018

Robust z-statistics in parentheses. Standard errors clustered by stocks.

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports panel regression results with AR(+1) as the dependent variable but with an unbalanced panel. We construct the dummy variable of three media platforms. AR(+1) means the abnormal return for the day after the news release. AR indicates the abnormal return on the day of the news release. This table reports panel regression results with AR(+1) as the dependent variable.

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