Fight or Flee? The Role of Firms' Connected Social Media Outlets

Zhiqian Jiang, Baixiao Liu, Yuchen Xu, and Bohui Zhang[*]

Abstract

We examine whether and how firms leverage social media outlets to counteract the impact of negative news coverage in traditional media. Using a sample of Chinese public firms with established connections to social media outlets, we find that the connected outlets actively promote favorable narratives about the firms immediately following unfavorable coverage in traditional media. This effect is more pronounced for firms with stronger incentives to stabilize stock prices or when managers face greater career concerns. Moreover, while traditional media coverage tends to highlight firms' short-term underperformance, connected social media outlets shift the focus toward their long-term development prospects. Our findings highlight the role of social media in proactive corporate management of media narratives.

Keywords: Social Media Outlet; Media Connection; Stock Price Stabilization; Managerial Career Concern; Media Narratives

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[*]Jiang (Email: zhiqian.jiang@xmu.edu.cn) is associated with the School of Management, Xiamen University, No. 422 Siming South Road, Xiamen, Fujian, P. R. China, 361005. Liu (Email: baixiaoliu@phbs.pku.edu.cn) is associated with the HSBC Business School, Peking University, University Town, Nanshan District, Shenzhen, P. R. China, 518055. Xu (Email: yuchen.xu@unsw.edu.au) is associated with the UNSW Business School, High Street, Kensington NSW 2052, Sydney, Australia. Zhang (Email: bohuizhang@cuhk.edu.cn) is associated with The Chinese University of Hong Kong, Shenzhen, 2001 Longxiang Boulevard, Longgang District, Shenzhen, P. R. China, 518172. We thank Anna Constantatos, Fuwei Jiang, Zhiming Ma, and participants at the 2025 Annual Meeting of the European Financial Management Association (EFMA 2025), 2025 China International Conference in Finance (CICF 2025), 2025 China Financial Research Conference (CFRC 2025), and workshop at the University of New South Wales (UNSW) for helpful comments. Jiang acknowledges support from the Youth Fund of National Natural Science Foundation of China (72302195).

1. Introduction

This study examines the proactive role that firms play in managing media narratives through social media outlets to mitigate the impact of negative news coverage by traditional media. In the landscape of corporate information environment, the interplay between firms and media outlets has grown increasingly complex. On the one hand, the scholarly inquiry illuminates the pivotal role played by the media in disseminating crucial corporate information to market participants, shaping their perceptions, and impacting both corporate decision-making and investor behaviors.[1] In particular, negative coverage in traditional media has long been recognized as a significant risk factor for corporations. Such negative coverage can lead to adverse outcomes, including regulatory intervention, diminished managerial compensation, and greater likelihood of executive turnovers (e.g., Dyck, Volchkova, and Zingales, 2008; Liu, McConnell, and Xu, 2017; Love, Lim, and Bednar, 2017; Baloria and Heese, 2018).

On the other hand, corporations are not mere passive subjects of media coverage. Instead, they can actively shape their public image through interactions with various media platforms (e.g., Ahern and Sosyura, 2014; Edmans et al., 2018; Ru et al., 2020). Traditionally, corporate responses to unfavorable media attention have been rooted in public relations efforts aimed at controlling traditional media narratives through direct engagement with journalists, press releases, and crisis management. Nowadays, however, the landscape of news dissemination has witnessed a transformative shift, moving from traditional newspapers, TVs, and websites to the pervasive realm of social media platforms. News consumers frequently obtain instant messages through social media channels such as Twitter in the United States and WeChat in China, driven by the unparalleled accessibility to and heightened reliance on mobile devices. The wide and rapid diffusion nature of social media has introduced new dynamics in corporate management of media narratives, providing firms with unprecedented channels to engage directly with consumers and stakeholders and thereby bypassing traditional media outlets.

We posit that corporations can leverage on their connections with social media outlets to mitigate the impact of negative traditional media coverage. By utilizing social media platforms, corporations can directly influence public sentiment, rapidly disseminate counter-narratives, and engage in real-time dialogue with their audience. This shift not only alters the power

[1] The former set of studies provides evidence that the media influence executive compensation (Core, Guay, and Larcker, 2008; Kuhnen and Niessen, 2012), corporate governance (Dyck, Volchkova, and Zingales, 2008) and Joe, Louis, and Robinson, 2009), capital allocation (Liu and McConnell, 2013), corporate fraud detection (Miller, 2006), and insider trading prevention (Dai, Parwada, and Zhang, 2015). The latter set of studies shows that the media impact aggregate stock market performance (Tetlock, 2007), specific stock returns (Tetlock, Saar-Tsechansky and Macskassy, 2008), mutual fund allocations (Fang, Peress, and Zheng, 2009), investor trading behavior (Engelberg and Parsons, 2011), and trading volume and intraday stock price volatility (Peress, 2014).

dynamics between traditional and social media but also has profound implications for corporate management of media narratives.

We examine the emerging social media outlets that corporations employ to counteract negative news coverage propagated by traditional media. Specifically, we attempt to address the following research questions: i) whether and how firms with social media connections combat negative traditional media coverage via social media outlets? and ii) what are the incentives and consequences of firms' proactive management of social media narratives to counter negative news coverage in traditional media outlets?

To investigate these inquiries, we analyze social media coverage of publicly traded companies in China through WeChat Official Accounts. We focus on the Chinese setting for two reasons. First, China presents a striking contrast between its highly regulated traditional media where institutional barriers explicitly prohibit corporate investment in and control of news organizations,[2] and its rapidly evolving social media landscape, which remains more commercially oriented and subject to less clearly defined regulation. Second, China's capital market is dominated by retail investors, who account for approximately 80% of stock trading volume.[3] These investors tend to be highly responsive to information disseminated through widely used platforms like WeChat, amplifying the potential impact of social media narratives.

Introduced by Tencent in 2011 as an instant messaging tool, WeChat has since evolved into an all-encompassing application with a wide array of features (e.g., messaging, social media functionalities, e-commerce capabilities, and mobile payment services) and has collected exceeding 1.3 billion monthly active users.[4] In 2013, WeChat introduced Official Accounts, a social media platform allowing users to amass followers, distribute content to subscribers, engage with their audience, and offer various services.

As of 2023, there are over 20 million active WeChat Official Accounts, with news consumption as a primary reason for following accounts. Appendix Figure A1 provides an example of a prominent WeChat Official Account, 36Kr, which focuses on financial and business news. We source WeChat articles from *Datayes*, a data vendor that collects articles from major financial media outlets via their WeChat Official Accounts and provides sentiment analyses using the attention-based convolutional neural network (CNN) model. Spanning from

[2] See, for example, China's 2018 Negative List for Market Access, which prohibits non-public capital from investing in certain media activities beyond permitted ownership thresholds and requires key media entities to remain solely or predominantly state-owned, including after public listing.

[3] According to the 2017 Shanghai Stock Exchange Statistical Yearbook, retail investors accounted for 85.62% of total trading volume in 2016—the beginning of our sample period (p. 625). As of the end of 2023, individual accounts with less than RMB 500,000 in capital still made up 80% of all accounts, based on the 2024 Yearbook.

[4] https://www.statista.com/statistics/255778/number-of-active-wechat-messenger-accounts/.

2016 to 2023, the database encompasses a substantial collection of over 1.25 million deduplicated WeChat news articles. These articles pertain to 5,274 Chinese A-share publicly traded companies, accounting for over 99% of the total market capitalization in China.

To identify corporate connections with social media outlets, we consider a public firm having a social media connection where the public firm directly holds shares in, or being held shares by, the entity operating the WeChat Official Account ("WeChat firm", thereafter); the public firm and the WeChat firm share key personnel such as the ultimate controller, shareholders, legal representatives, and top management team members; or the public firm and the WeChat firm have common ownership in a third-party firm. We find that the fraction of Chinese public firms identified to have established a connection with social media outlets increases monotonically from 7.96% in 2016 to 14.96% in 2023, representing roughly 34% of the total market capitalization as of July 2023.

We first examine whether firms with social media connections combat negative traditional news coverage via social media outlets. To begin, we identify 286 firm-date events where the average tone of traditional news articles covering a firm falls in the bottom decile.[5] This generates a sample of 25,580 article-firm observations from 54 Chinese public firms with social media connections between 2016 and 2023. Focusing on WeChat articles published within the [-10, +10] event window, we apply a Difference-in-Differences (DiD) approach, where the first difference compares pre- and post-event windows, and the second difference distinguishes articles connected to the focal firm from those that are not. We find that articles from connected WeChat accounts exhibit a more positive tone post-event compared to those from unconnected accounts. We further show in the dynamic DiD analyses that the effect is pronounced only in the post-event period. To verify that this pattern is specific to negative events, we repeat the analysis for 234 firm-date events in which traditional media tone falls in the top decile. In this placebo sample, we find no significant post-event tone difference between connected and unconnected accounts. Overall, these results are in line with the notion that firms with social media connections combat negative traditional news coverage by shaping positive narratives through social media outlets.

We perform a series of robustness checks to validate our baseline results. Specifically, we randomize placebo treated firm, perform placebo tests by shifting the treatment time backward

[5] While our sample size may appear limited, it represents the largest dataset meeting our criteria for conducting the DiD analysis. Specifically, the DiD framework requires that each event must have at least one connected article and one unconnected article in both the pre- and post-event windows. Additionally, to avoid confounding results, we exclude events that occurred within 15 days of a prior event for each firm.

one to five periods, employ alternative event identification strategies, apply alternative event windows, require alternative minimum lag days between events for sample construction, require non-missing connected and unconnected WeChat articles only in the post-event window, and implement stricter fixed effects. Our baseline findings are robust to these additional tests. In addition, we find that the favorable narratives disseminated through connected social media outlets have a tangible impact on stock prices. Specifically, our event-time analysis shows that, on days when firms are covered by at least one connected WeChat article following a negative news event, the daily abnormal stock return increases by approximately 0.3 percentage points relative to other days. These findings provide direct evidence that firms can leverage connections with social media outlets to dampen the adverse market impact of negative news.

Next, we examine how firms with social media connections combat negative traditional news coverage through social media outlets. Utilizing machine-learning-based textual analysis, we label topics of traditional news articles on the event date and WeChat articles published within the [0, +10] window for each of the 286 events. We find that traditional news articles and unconnected WeChat articles tend to focus on similar topics, often highlighting events such as short-term poor market assessment and financial performance. In contrast, connected WeChat accounts focus on topics related to long-term firm development such as corporate strategy, R&D, cooperation, human resources, and corporate social responsibility (CSR) activities. This disparity in topic coverage suggests that firms with social media connections adopt a diversion strategy to reshape the narrative following negative traditional media coverage.

We then explore firms' incentives to counter negative traditional media coverage through social media. We find that our baseline results are more pronounced when managers have greater incentives to stabilize stock prices, such as during an upcoming acquisition or when large shareholder/management interests are more closely tied to stock market performance (e.g., high ownership by large shareholders/management, share pledges by the ultimate controller, or high management options). Additionally, the effect is more pronounced when managers face more significant career concerns, as indicated by poorer firm performance, higher stock price volatility, and younger CEOs.

Finally, we examine the effectiveness of corporate connections with social media outlets in stabilizing stock prices and protecting managerial careers. In particular, we investigate whether firms with social media connections perform differently than those without social media connections. Using firm-level regressions, we find that firms connected with social media outlets experience more positive market reaction around acquisition events, higher insider trading profits, and a lower likelihood of CEO or chairman turnover. The results indicate that through connections with social media outlets, firms can actively fight back negative traditional news coverage to stabilize stock prices and protect managerial careers.

Our study contributes to two strands of literature. First, our study contributes to the literature on the role of social media in capital markets. Much of this research characterizes social media coverage as an independent and decentralized source of investor-relevant insights that complements traditional intermediaries by uncovering overlooked information and enhancing market transparency (e.g., Chen, De, Hu, and Hwang, 2014; Blankespoor, Miller, and White, 2014; Ang, Hsu, Tang, and Wu, 2021). We contribute to the existing literature by providing empirical evidence that firms can leverage social media platforms to influence public perception and counteract negative narratives propagated by traditional media. Specifically, we demonstrate that firms' engagement with social media outlets can result in more favorable coverage. Thereby, corporate use of social media not only mitigates the adverse effects of negative traditional media coverage but also helps firms regain control over their public narratives, potentially altering investor sentiment and market responses.

Second, we extend the research on firms' proactive management of media coverage by identifying a novel channel for shaping public perception. Prior studies have extensively examined how firms influence traditional media through mechanisms such as advertising, official press releases, cross-holding institutions, and executives' social media activity (e.g., Solomon, 2012; Gurun and Butler, 2012; Bushee and Miller, 2012; Ahern and Sosyura, 2014; Xu, 2018; Gurun, 2020; Hossain and Javakhadze, 2020; Ru et al., 2020; Yan et al., 2023; He et al., 2025). Our research, however, breaks new ground by focusing on the role of social media outlets themselves as corporate tools of favorable narratives. In particular, rather than focusing on how firms communicate directly through their own channels, we examine how firms can leverage established relationships with independent social media outlets to counterbalance negative coverage in traditional media. This perspective highlights a previously underexplored channel of indirect influence. By emphasizing the active role of external social media outlets beyond firms' proprietary accounts, our study shows how third-party narratives can be deployed to reinforce corporate reputation and shape investor sentiment in the wake of unfavorable news reports. In doing so, our research broadens the corporate media management literature by illuminating the intermediary function of social media, revealing how firms can selectively enlist these platforms to mitigate critical narratives from traditional media.

2. Sample and data

Our analyses combine novel datasets of financial news articles from both traditional media and social media in China, along with detailed information on Chinese listed firms. The sample spans January 2016 to July 2023, a period during which major Chinese social media platforms, notably WeChat, experienced significant growth. We provide a full explanation of the sample and data construction process in the methodology section. For definitions of all variables used, please refer to Appendix Table A1.

2.1 WeChat articles and firms' connection to social media outlets

Our analysis begins with a dataset of financial news published on WeChat Official Accounts from *Datayes*, a leading data platform and information service provider in China. As China's primary social media platform, WeChat introduced the Official Account (*Gongzhong Hao*) feature in 2013, which had achieved substantial market penetration by 2016.[6] Over the period from January 2016 to July 2023, *Datayes* collected over five million articles published by influential WeChat accounts.

Specifically, we focus on the subset of articles published by corporate-operated financial media accounts, excluding those from individuals, governments, or pubic firms' own official accounts.[7] This selection leaves us with around 700 WeChat accounts whose articles cover 5,274 public firms, representing 99.15% of the total market capitalization in China as of July 31, 2023 (Appendix Table A2).[8] For simplicity, we refer to these corporate-operated WeChat entities as "WeChat firms" throughout the study. In our study, a public firm is considered "connected" to a social media outlet if it has a linkage to at least one WeChat firm.

We define social media connections through three primary channels: i) direct investment relationships, where connections exist if a public firm holds shares in a WeChat firm or vice versa; ii) personnel-based connections, where the public firm and the WeChat firm share at least one key personnel, such as an ultimate controller, shareholder, legal representative, or

[6] "Official Account" is the formal product name designated by WeChat and does not connote any governmental or authoritative status. In practice, any organization or individual can register one. These accounts operate similarly to blogs or publisher pages on other global social media platforms, allowing entities to build a subscriber base.

[7] This focus allows us to establish a measure of firm-social media connections that captures relationships between firms and third-party media, rather than between firms and individuals or government entities. Additionally, by excluding firms' own official accounts, we aim to emphasize covert connections with social media outlets, which are distinct from the more transparent public releases issued directly by firms.

[8] Our sample of approximately 700 WeChat firms is derived from an initial list of over 3,543 accounts curated by *Datayes*. The vendor selects these accounts based on their influence (e.g., high readership or rapid growth), financial news focus, and relevance to institutional clients. We further refine this list by excluding: i) firms' own official accounts to distinguish from direct corporate communication; ii) government-run accounts; and iii) individual-operated accounts, which we identify using *Qichacha* business registration data. The resulting sample is thus designed to capture influential, third-party, corporate-operated social media outlets.

member of the top management team; and iii) common ownership links, where both the public firm and the WeChat firm have ownership stakes in a third-party entity.

To determine whether a firm has the connections described above with WeChat firms, we use data from *Qichacha.com*, one of China's largest repositories of comprehensive business information. While mutual investment connections are directly accessible through a firm's current and historical investment activity profile on *Qichacha.com*, identifying personnel-based and common ownership connections requires a more meticulous approach. We uncover these indirect connections through a manual procedure. Specifically, for both public firms and WeChat firms, we extract historical biographies of all their key personnel and collect information such as their positions in the firm, investment activities, as well as the starting and ending dates of each position/activity. We then cross-reference affiliations and dates to identify any overlapping periods.

To illustrate examples of connection, Panel A of Appendix Figure A2 shows the connection between Wu Xiaobo Channel, a leading financial WeChat account, and Wufangzhai (stock ID: 603237.SH), a public firm specializing in traditional rice products. They have been connected through a shared independent director since March 2018. Panel B of Appendix Figure A2 provides an example of investment-based link: the connection between CRIC Real Estate Research, a leading real estate analytics media account, and the property developer Taihe Group (stock ID: 000732.SZ), established through Taihe's direct investment in the parent company of CRIC.

For each public firm-year, we construct a binary variable *Connect*, which takes the value of one if the firm has established any of the three types of connections with at least one WeChat firm, and zero otherwise. Once an initial connection is made, we assume it persists, even if there are temporary or permanent interruptions in the observable connection. For example, if a public firm was connected to a WeChat firm through personnel, we assume such connection remains in place even if the key personnel resign. This assumption accounts for the possibility that other unobservable connections may emerge after the initial link is established.

Table 1 provides an overview of the prevalence and trends in firm-social media outlet connections. From January 2016 to July 2023, 14.66% of our sample public firms (730 out of 4,978) have established a connection with at least one WeChat firm. By July 2023, these connected firms collectively accounted for 33.91% of the total market capitalization of publicly traded firms in China. Over the sample period, the prevalence of social media connections significantly increased, rising from 7.96% in 2016 to 14.96% in 2023.

[Insert Table 1 about here]

Appendix Table A3 provides a detailed breakdown of the industry distribution for public firms connected to social media outlets. Notably, 67% of financial firms are connected to social media outlets, which aligns with expectations given the significant involvement of investment firms that naturally form connections with numerous other entities. However, social media connections are also widespread across other industries. Specifically, real estate (33%), transportation, warehousing, and postal services (33%), and culture, sports, and entertainment (31%) emerge as the three most connected sectors. Additionally, over one-fifth of firms in electricity, heat, gas, and water production and supply (29%), education (25%), health and social work (24%), leasing and business services (24%), accommodation and food services (22%), and wholesale and retail trade (21%) are also connected to social media outlets. With few exceptions, most other industries report social media connections exceeding 10%. These findings highlight the pervasive and widespread nature of social media connections across a broad range of industries.

In Appendix Table A4, we present a selection model analysis to examine which types of firms are more likely to establish connections with social media outlets. Using a linear probability regression model, we find that larger and older firms, those with lower book-to-market ratios, and state-owned enterprises are more likely to form such connections. These findings suggest that firms with greater market power and better valuation are more likely engaging in employing social media outlets to shape their perceptions.

2.2 WeChat article sentiment

We conduct our baseline analyses using article-firm level regressions, where the main dependent variable is the sentiment of the article toward the public firm in question. The article-firm sentiment scores are provided by *Datayes*, which employs a BERT-CRF model to identify firms mentioned in each article. Each article-firm pair is then assigned a relatedness score ranging from zero (least relevant) to two (most relevant). We retain article-firm pairs that either focus exclusively on the focal firm (relatedness=two) or primarily discuss the firm while mentioning others (relatedness=one).

After identifying relevant firms for each article, *Datayes* applies a Natural Language Processing (NLP) model—specifically, an attention-based CNN model—to assign a sentiment score to each article-firm pair. The score is calibrated on a scale from minus one (most negative) to one (most positive). In regression analyses, we weigh the sentiment score by the relatedness score to reflect the extent to which readers receive information about the focal firm from the article.

2.3 Traditional news articles and negative news events

Our investigation into whether and how public firms leverage their social media connections to counteract negative traditional media coverage focuses on events marked by particularly negative traditional media coverage. To identify such events, we utilize the *Datayes* dataset that covers over 47 million deduplicated financial news articles from traditional media outlets. This dataset's structure, which mirrors that of the WeChat article dataset, provides a key advantage in maintaining consistency and comparability in article-firm relatedness score and sentiment assessments across traditional and social media platforms.

We define firm-dates with particularly negative traditional media coverage (henceforth, "events") as instances where the daily average relatedness-adjusted tone of traditional news articles falls within the bottom decile of that day.[9] To improve the interpretative precision of our DiD analyses specified in Section 3.1, we focus on the [-10, +10] event window and require each event to include at least one connected article and one unconnected article in both the pre- and post-event windows. To avoid confounding effects, we further exclude events that occurred within 15 days of a prior event for each firm. This process yields a sample of 286 firm-date events from 54 Chinese public firms during the period of 2016 and 2023, pertaining to 2,019 traditional news coverage on the event date and 25,580 WeChat article-firm observations over the [-10, +10] window.

Appendix Table A5 compares the 54 firms' basic financials to those of other public firms. Consistent with the selection analysis results in Appendix Table A4, connected firms in our sample tend to be slightly larger and older, with higher leverage, higher book-to-market ratios, and a higher likelihood of state ownership. Appendix Figure A3 revisits the case of Taihe Group, a connected firm previously introduced in the paper, and illustrates articles published around its negative traditional news coverage on August 14, 2020.

Table 2 presents summary statistics for articles published around the event day and the social media connection indicator used in our baseline regression. Specifically, Panel A reports statistics for traditional news articles published on the event day. The average firm receives 7.1 articles from traditional news outlets, with a tone score of -0.137, indicating a generally negative sentiment. Panel B focuses on WeChat articles published over the [-10, +10] event

[9] Our results are robust in alternative cutoffs as shown in the robustness section.

window. During this 21-day period, the average firm receives 91.9 WeChat articles: 13.8 from connected accounts (6.4 pre-event and 7.4 post-event) and 78.0 from unconnected accounts (35.2 pre-event and 42.9 post-event). The average tone of WeChat articles over the [-10, +10] window is 0.055, likely reflecting the lack of consistently negative coverage in the pre-event window. Panel C provides statistics for the *Connect* indicator. On average, 13.8% of WeChat articles published during the event window are from connected accounts.

[Insert Table 2 about here]

2.4 Topics of news articles

To investigate how connected firms counteract negative news coverage in traditional media through social media, we conduct a textual topic analysis on both traditional news articles and WeChat articles. For each article-firm pair, we use large language models (LLMs) to assign the most relevant topic based on the context in which the specific firm is mentioned.

We categorize news topics into the following nine categories: financial performance (e.g., net profits, cash flows, and debt conditions), investment/financing activities (e.g., acquisitions, asset restructuring, and capital-raising events), production and sales activities (e.g., inventory, raw materials, and advertising expenditures), operating activities (e.g., changes in core business scope, new product launches, and operational expansions), equity structure (e.g., shareholder pledges, dividends, and stock splits), market assessment and ratings (e.g., stock price changes, analyst evaluation, and rating agency updates), R&D, innovation, and human resources (e.g., patent filings, organizational restructuring, and executive hires), strategy, cooperation, and CSR (e.g., corporate alliances, partnerships, and charitable donations), negative events (e.g., regulatory warnings, lawsuits, and bankruptcy), and industry policies and macro-environment (industry trends, economic outlooks, and global market shifts). For detailed definitions and content of the news topic categories, please refer to Appendix Table A6.

2.5 Other firm characteristics and activities

We obtain data on stock market prices and firm financial characteristics—such as firm size, firm age, book-to-market ratio, return on assets (ROA), leverage, buy-and-hold abnormal return (BHAR), stock volatility, stock turnover, institutional ownership, and a state-owned enterprise (SOE) indicator—from either the *China Stock Market & Accounting Research* (*CSMAR*) or the *Chinese Research Data Service* (*CNRDS*), two widely used databases for research on China's financial markets.

To examine firms' motivations for establishing social media connections, we also analyze corporate acquisition, insider trading, and CEO/Chairman turnover activities. Specifically, data on acquisition activities are sourced from the *China Listed Firm M&A and Restructuring Research Database* by *CSMAR*; data on insider trading are obtained from the *Insider Trading Database of Chinese Companies* by *CNRDS*; and data on CEO/Chairman turnover come from the *China Listed Firm's Corporate Governance Research Database* by *CSMAR*. Data construction and sample details are discussed in the relevant sections.

3. Whether firms counteract negative traditional news coverage using social media

In this section, we aim to address the first research question: do firms with social media connections use social media outlets to counteract negative news coverage in traditional media?

3.1 Baseline DID

Based on a sample of 286 negative events covering 25,580 firm-WeChat articles from 2016 to 2023 identified in Section 2.2, we first conduct an article-firm level DiD analysis based on the following model:

$$\begin{aligned} &\textit{WeChat tone}_{i,j,t} = \alpha + \beta \textit{Connect}_{i,j} \times \textit{Post}_t + \gamma \textit{Connect}_{i,j} + \textit{year-month FE} + \textit{event FE} \\ &+ \textit{event-date FE} + \textit{WeChat firm FE} + \varepsilon_{i,j,t}, \end{aligned} \tag{1}$$

where the dependent variable is the tone of WeChat article i toward firm j, with tone scores ranging from minus one to one (a higher score indicates a more positive tone), as assigned by *Datayes*. The article publication date is denoted as t. The DiD variable follows a "*Treated* × *Post*" structure, where *Treated* is a "*Connect*" dummy equal to one if the article i is authored by a WeChat account connected to firm j, and zero otherwise. *Post* is a dummy equal to one if the article i is published within the post-event window, and zero otherwise.

This article-firm-level approach enables us to incorporate a granular set of fixed effects to control for covariates thoroughly. Specifically, we include: year-month fixed effects to capture variations in macroeconomic and market conditions; event fixed effects to control for event-specific factors, which absorb firm-level fixed covariates; relative-to-event-date fixed effects to account for distance-to-event covariates; and WeChat firm fixed effects to control for time-invariant characteristics specific to each WeChat account. We also cluster standard errors at the event level.

Our primary focus on the model is the estimated coefficient of *Connect* × *Post*, where a positive sign indicates that connected WeChat accounts publish articles with more positive sentiment than unconnected accounts following a highly negative traditional media event. The regression results reported in Column 1 of Table 3 support our conjecture. Following negative traditional media coverage events, the tone of articles from connected accounts increases by 0.013 relative to unconnected accounts. The effect is economically meaningful, representing 23.6% of the sample mean, *WeChat tone* (0.055). Additionally, the estimated coefficient of *Connect* is statistically insignificant, suggesting that connected articles do not consistently display higher tones in the pre-event window. That is, firms leverage their connections only after negative coverage by traditional media outlets.

[Insert Table 3 about here]

As a placebo test, Column 2 of Table 3 examines the response of connected social media accounts to positive news events. These events are constructed symmetrically to our primary sample, defined as firm-dates where the average tone of traditional news articles falls within the top decile for that day. All other sample selection criteria, such as the event window and pre/post article requirements, are identical to those specified for negative events in Section 2.3. The results show no discernible difference in tone between connected and unconnected articles around positive events. This suggests that corporate use of connected media is primarily motivated by the need to counteract negative news, as the consequences of adverse coverage are particularly harmful to firms.

[Insert Figure 1 about here]

Panel A of Figure 1 depicts the coefficients of a dynamic DiD model, where we interact *Connect* with various relative-to-event date time dummies. The pattern validates the parallel trends assumption, indicating no significant differences in tone between connected and unconnected articles prior to the event date. On the event date, firms experience negative coverage in traditional news media, and the treatment effect becomes immediately significant on days zero and one. This finding suggests that firms promptly utilize social media connections to counteract negative news coverage by disseminating more favorable narratives. These efforts aim to send positive signals to the market, to mitigate potential reputational damage, and to minimize negative traditional media coverage that could adversely affect stock prices and investor confidence.

Panel B of Figure 2 further illustrates the raw level of average daily relatedness-adjusted sentiment over the event window for both connected and unconnected articles. In particular, prior to the event date, tone scores for connected and unconnected articles are similar. On the event date, the tone of unconnected articles sharply declines, likely reflecting their alignment with the negative news content reported in traditional media. In contrast, articles from connected accounts display significantly higher sentiment scores immediately following the event. These sentiment scores gradually converge and intersect by day eight.

3.2 Robustness

One potential concern with our analyses is that our sample events are selected by design, which could introduce selection bias stemming from the criteria used to identify negative traditional media coverage events. To address this concern, we perform a battery of tests to verify the robustness of our baseline results. These tests follow Equation (1) but apply several model variations, including assigning placebo treatments or event times, altering sample construction methods, adjusting event windows, and modifying fixed effects. The results of these robustness checks are presented in Figure 2 and Table 4.

[Insert Figure 2 about here]

We first conduct an in-space placebo test by repeating 500 times our baseline regression specified in Eq. (1), randomly assigning a value of one to the *Connect* indicator while maintaining the proportion of connected articles consistent with the actual sample. Figure 2 shows the histogram distribution of the estimated coefficients for *Connect* × *Post*. As illustrated, the distribution centers around zero and rarely exceeds 0.01, whereas the actual coefficient is 0.013 (as shown in Table 3). This result suggests that the observed treatment effect is less likely driven by random chance or spurious correlations, reinforcing the validity of our findings.

[Insert Table 4 about here]

In Panel A of Table 4, we conduct an in-time placebo test by shifting the event date backward, with placebo day zero set to correspond to days minus five to minus one in the actual sample. Following standard in-time placebo testing, we exclude articles in the post-event window to ensure only unaffected observations are used. The results show that the estimated coefficient of *Connect* × *Post* becomes small and statistically insignificant, indicating that the timing of positive articles published by connected accounts is non-random. That is, firms are selectively and purposefully timing their social media responses to align with periods of heightened negative media coverage in traditional outlets, effectively countering unfavorable narratives at critical moments.

In Panel B, we modify the event selection criteria. Column 1 identifies events where a firm's daily average relatedness-adjusted tone in traditional news falls within the bottom quartile, rather than the bottom decile used in the baseline analysis, while keeping all other selection design parameters unchanged. This broader selection criterion expands the sample to 627 events covering 83 firms, increasing the article-firm observations in the regression to 64,774. The result remains consistent. The coefficient of 0.012 is closely aligned with the baseline coefficient estimate of 0.013.

In Column 2, the selection process is modified by aggregating all firm-article pairs and selecting those with bottom-decile tone across the entire sample period, rather than identifying the bottom-decile sample within each day. This approach results in a consistent outcome, with the effect magnitude larger than that observed in the baseline regression, further reinforcing the robustness of our findings.

In Column 3, we define negative articles using an alternative approach: a firm-day is classified as experiencing a negative traditional news coverage shock if the daily average tone of related traditional news articles falls more than one standard deviation below the firm's average tone from the previous year. Unlike previous approaches that compare news tones across different firms, this mechanism focuses on the deviation of a firm's news tone from its historical norm, offering a more tailored and firm-specific measure of unexpected negative coverage. Again, the DiD coefficient remains robust, with an even larger effect size than the baseline results.

Panel C modifies the event window and spacing criteria. Columns 1–2 adjust the event window from [-10, 10] in the baseline sample to narrower [-5, 5] and wider [-20, 20] windows, respectively. Columns 3–4 impose a minimum time interval of 20 and 30 days between consecutive events, instead of the baseline 15 days. All results remain robust, with particularly strong effects observed within the [-5, 5] window, aligning closely with our baseline findings, as illustrated in Figure 1.

Panel D further tests sample and fixed effects adjustments. In the baseline sample, we require at least one connected article and one unconnected article in both the pre- and post-event windows to ensure a robust DiD estimation. In Column 1, we relax this sample selection criteria by allowing for events where connected or unconnected articles are missing in the pre-event window. This approach expands the sample size by threefold, yet the estimated coefficient (0.016) remains close to the baseline, demonstrating the robustness of our findings to this sample selection criterion. In Column 2, we apply stricter fixed effects by including event × relative-date-to-event fixed effects. These fixed effects absorb year-month, event, and relative-date-to-event fixed effects, controlling for unobserved heterogeneity more comprehensively. The results remain both statistically and economically significant, with an even larger effect size, further reinforcing the robustness of our findings.

Parallel trend figures for all above-mentioned robustness checks are shown in Appendix Figure A4. Overall, these robustness tests indicate a consistent pattern: firms with social media connections appear to leverage these connections by disseminating significantly more positive news immediately after receiving negative coverage in traditional media.

3.3 Stock market reaction to positive social media narratives

We next examine whether the favorable narratives published by connected social media accounts translate into a tangible stock market impact. To do so, we conduct a daily event-time analysis for the 286 negative news events, focusing on the post-event window [0, +10]. This creates a data structure of 3,146 firm-day observations (286 events × 11 days). We further exclude days with no WeChat coverage, resulting in a final sample of 2,346 observations.

We estimate regressions to examine how the presence of connected WeChat coverage influences market reactions to negative news events. Specifically, the dependent variable is either the daily abnormal stock return (*AR*), calculated as the firm's daily raw return minus the value-weighted market return, or the cumulative abnormal returns (*CAR*) over the [0, +1] and [0, +2] windows. The key independent variable is a firm-day indicator, *Connected day*, which equals one if the firm is covered by at least one connected WeChat article on that day, and zero otherwise. All regressions include year-month fixed effects and public firm/event fixed effects to account for time-varying market conditions and unobserved firm/event-level heterogeneity.

[Insert Table 5 about here]

Table 5 presents the regression results. On days featuring at least one connected article, firms experience a significantly more positive market reaction. Specifically, the daily abnormal return is approximately 0.3 percentage points higher on connected days. This effect is not only statistically significant but also economically meaningful, representing a sizable increase compared to the mean daily abnormal return of -0.1 percentage points in our sample. These findings provide direct evidence that corporate use of connected media can effectively mitigate the adverse price impact of negative news.

4. How firms counteract negative traditional news coverage using social media

We have demonstrated in the previous sections that firms can leverage connected social media accounts, characterized by notably more positive tones, to counteract negative news coverage in traditional media. In this section, we address a critical follow-up question: beyond adopting a more positive tone, do connected social media outlets differ from traditional media outlets in their choice of article topics? Specifically, do connected social media outlets discuss the same topics as traditional media but with a more favorable tone, or do they emphasize different topics to redirect readers' attention?

To investigate this question, we conduct a detailed textual analysis of article content across three news sources: traditional media outlets, connected WeChat accounts, and unconnected WeChat accounts. Because our focus is on how social media responds after the emergence of negative traditional news coverage, we analyze traditional news articles published on the event day and WeChat articles during the [0, +10] post-event window. The inclusion of unconnected WeChat accounts allows for a more comprehensive comparison, offering deeper insights into the unique narratives employed by connected WeChat accounts. Articles are categorized into nine distinct topics, with detailed definitions provided in Appendix Table A6.

[Insert Table 6 about here]

To motivate our discussion, we reference an example in Appendix Figure A2. Taihe Group, a firm linked to a social media outlet, experienced a negative traditional news event on August 14, 2020, due to earnings miss. Column 1 in Appendix Figure A3 lists the titles of all traditional news articles covering the firm on August 14, 2020, with negative-tone articles marked in red, neutral articles in black, and positive-tone articles in green. Notably, there was no social media coverage on the event day, underscoring the dominance and spontaneity of traditional news in financial reporting.

Columns 2–4 display news coverage from the following three days, August 15–17, 2020. On August 15 and 16, two unconnected social media outlets reported on the firm with a negative tone, covering similar themes of disappointing earnings performance. On August 17, however, a connected social media outlet published a positive-tone article titled "Taihe Group: Attracting Vanke Strategic Investment Sends Positive Signal". This article shifted the narrative to highlight other favorable, long-term developments, potentially aiming to redirect readers' attention and emphasize a brighter outlook for the firm. As illustrated by this example, we hypothesize that connected articles tend to shift readers' attention by focusing on topics related to the firm's optimistic future prospects.

We formally test this hypothesis in Table 6. Panel A presents the distribution of article topics, measured by both number and percentage of articles, across the three article samples. Columns 1–2 display the topic distribution for traditional news articles published on the event day, ranked by topic prevalence. Negative coverage is primarily associated with topics such as market assessment and ratings (e.g., declining evaluations by analysts or investors) and poor financial performance (e.g., falling net profits). Columns 3–4 report the topic distribution for unconnected WeChat articles published during the post-event window. Here, market assessment and ratings, along with financial performance, remain the top topics, consistent with the pattern observed in traditional media.

Columns 5–6 further present the topic distribution for connected WeChat articles published during the post-event window. Notably, topic distribution diverges significantly, with a higher proportion of articles focusing on industry policies and the macroeconomic environment—topics less directly related to the firm itself. Additionally, coverage of long-term development themes, such as R&D, innovation, human resources, strategy, cooperation, and CSR, increases substantially. These patterns validate our conjecture that connected firms on WeChat actively shift the narrative toward emphasizing their future prospects and positive developments.

In Panel B, we perform regression analyses based on the sample of WeChat articles published in the post-event window. The dependent variable, *Same label*, is a binary indicator that takes a value of one if the article topic aligns with the event topic—defined as the most prevalent topic among traditional news articles covering the firm on date zero, and zero otherwise. The results indicate that connected WeChat articles are significantly less likely to address the same topics as traditional news, lending further support to our conjecture that connected firms shift the narrative to focus on positive and forward-looking themes.

5. Incentives and effectiveness of counteracting negative traditional news coverage using social media

Why are firms incentivized to leverage connected social media, and how effective is the proactive management of media narratives in achieving their intended outcomes? In this section, we explore and evaluate two key incentives that drive firms to utilize social media connections in response to negative traditional media coverage—stabilizing stock prices and mitigating managerial career concerns—and assess the effectiveness of such counterreactions.

5.1 Incentives

Prior studies show that negative media coverage can adversely affect stock prices (Tetlock, 2007), posing significant challenges for firms engaged in significant investment or financing activities. Building on this notion, we conjecture that a key motivation for firms' proactive social media management is to stabilize stock prices, particularly when preparing for high-stakes transactions. Given that mergers and acquisitions (M&As) are among the most important investment activities for firms, and a low stock price can weaken their negotiating position in such deals (e.g., Savor and Lu, 2009), we first examine whether the treatment effect is more pronounced when firms are preparing for an M&A transaction.

To test this, we split our sample firms into two groups based on whether a firm has a planned M&A transaction within the next three months. "Planned" transactions are identified ex post as those announced within three months following a negative traditional news coverage event. We then repeat our baseline DiD analyses separately for these two subsamples. Columns 1-2 in Panel A of Table 7 report the results. We find that although the coefficients for both subsamples are statistically significant, their magnitudes differ substantially. For firms with planned acquisitions, the estimated coefficient for *Connect* × *Post* is 0.059, compared to 0.013 for firms without planned acquisitions. This significant difference in magnitude underscores the heightened impact of proactive social media management for firms preparing for imminent acquisitions. While the sample size of firms with upcoming acquisitions is relatively small—since only a limited number of events meet our DiD design criteria within the short window before an M&A deal—these results provide supportive evidence that firms with upcoming acquisitions have a heightened incentive to counteract negative traditional news coverage.

[Insert Table 7 about here]

Beyond major corporate investment decisions, firms are also more likely to prioritize stock price stabilization when the interests of their large shareholders or managers are closely tied to market performance. In these scenarios, fluctuations in stock prices directly impact the financial well-being of these stakeholders, creating a strong incentive for them to mitigate price volatility. Stable stock prices not only preserve the value of their investments but also ensure the firm's continued access to capital markets and maintain its reputation among investors.

To capture the extent to which shareholder and managerial interests are tied to firm market performance, we analyze shareholder/managerial ownership, share pledges, and management options of the firm. Specifically, a firm's shareholder interests are considered closely tied to market performance if its largest shareholder's ownership stake is in the top tercile across all firms in the year, or if the ultimate controller has pledged shares. Similarly, management interests are considered closely tied to market performance if management ownership is in the top tercile in the year or if the management team holds stock options.

In Panel A of Table 7, we perform subsample analyses to compare the effect of social media connection between groups where the interests of large shareholders (Columns 3–4) or managers (Columns 5–6) are closely tied to market performance and those where they are not. As expected, we find that connected articles exhibit a more positive tone when key personnel have a vested interest in firm market performance. Notably, in the subsample where managers' interests are less aligned with firm performance, the estimated coefficient for *Connect* × *Post* is small and statistically insignificant, indicating a diminished use of social media in such cases.

Overall, the above analyses support the hypothesis that firms with a strong incentive to stabilize stock prices—as captured by the presence of planned M&A deals and the alignment of key personnel interests with market performance—are more likely to leverage connected social media outlets. These firms issue more positive connected articles to counteract negative coverage in traditional media, effectively mitigating potential adverse impacts on their market valuation.

An extension of the stock price stabilization motivation is the concern over managerial careers, as stock market performance is a critical factor in their performance evaluation (e.g., Coughlan and Schmidt, 1985; Murphy, 1985; Warner, Watts, and Wruck, 1988; Jensen and Murphy, 1990; Jenter and Lewellen, 2021). Poor stock performance, often amplified by negative media coverage, can expose managers to increased scrutiny from shareholders, potential damage to their professional reputation, and a heightened risk of turnover (e.g., Farrell and Whidbee, 2002). These stakes create strong incentives for managers to take proactive measures, such as leveraging connected social media outlets, to counteract negative publicity and protect their positions.

We use three proxies to capture scenarios with heightened managerial career-concern: poor operating performance, defined as firms in the bottom tercile of ROA within their industry in the previous year; large stock price volatility, defined as firms in the top tercile of stock price volatility in the previous year; and short CEO tenure, defined as CEOs with less than two years in their role at the start of the year. The underlying assumption is that when operating performance is poor, stock price volatility is high, or the CEO is new to the role, career concerns become intensified, increasing the need for positive media coverage to stabilize stock prices. Using similar subsample analyses, we report results in Panel B of Table 7. All results provide supportive evidence for our hypothesis.

5.2 Effectiveness

In Section 5.1, we have identified three key scenarios where firms are more likely to leverage social media connections to counter unfavorable traditional news coverage: when approaching a merger, when insider interests are closely tied to market performance, and when managerial career concerns are heightened. Building on these findings, we now examine whether social media connections effectively achieve their intended outcomes. Specifically, we assess whether these strategies enhance M&A performance, increase insider trading profits, and reduce the likelihood of CEO or chairman turnover. To address sample size limitations and provide a comprehensive evaluation, we adopt a broader firm-level analysis, enabling us to explore the wider implications of social media connections in achieving these objectives.

In the case of M&A, the number of deals announced following a negative news event is limited. Therefore, we expand the sample to include all 9,463 M&A deals announced by Chinese public firms between 2016 and 2023 with a deal value no less than RMB 10 million, and test whether connected firms achieved higher cumulative abnormal returns (CAR) for these deals. Specifically, we regress *CAR* on *Connect*, where *CAR* is the cumulative abnormal return over the [-1, 1] window for each deal, and *Connect* is an indicator equals to one if the acquiring firm has established a social media connection in the year prior to the merger announcement, and zero otherwise.

[Insert Table 8 about here]

Panel A of Table 8 reports the regression results. Given that firms establish connections with social media outlets over time and may make multiple acquisitions over the sample period, we are able to include firm fixed effects. This allows *Connect* to capture the effect of social media connections independently of other firm-level covariates. Across Columns 1 to 3, we vary the fixed effect specifications, and the results remain robust. Firms with social media connections show an abnormal merger return that is 0.015 higher than unconnected firms. This effect size is substantial, accounting for 29.4% of the sample standard deviation (0.051).

Panel B of Table 8 examines the payoff of social media connections on key personnel's personal interests, as measured by insider trading profits. Specifically, we source insider trading records for our sample firms during the sample period from the *Insider Trading Database of Chinese Companies* by *CNRDS*, which provides details on insider trading dates, firms, and average transaction prices. Following Skaife, Veenman, and Wangerin (2013), we measure insider trading profits based on the annualized "future" returns at the time of insider trading. We calculate six-month (or 12-month) annualized returns by comparing the stock price exactly six (or 12) months after the trade and the insider transaction price. For robustness, we also use the average price over the subsequent six or 12 months to mitigate potential bias from daily price fluctuations. The results indicate higher insider trading profits for connected firms, suggesting that key personnel may leverage social media connections to influence stock market prices for personal gain.

In Panel C of Table 8, we examine the impact of social media connection on key personnel's career concerns, using CEO/Chairman turnover as the dependent variable. Specifically, turnover is defined as a dummy indicating whether the CEO/Chairman leaves the firm within the next two or three years. The results show that CEOs and chairmen of connected firms are significantly less likely to leave the firm compared to those at unconnected firms. This suggests that CEOs and chairmen may leverage social media to stabilize stock prices, thereby mitigating their career risks.

6. Conclusion

This study sheds light on how corporations leverage their connections with social media outlets to mitigate the impact of adverse news coverage from traditional media. Focusing on Chinese public firms with connections to social media platforms, particularly WeChat Official Accounts, we observe that firms use these connected outlets to positively shape public narratives following unfavorable coverage in traditional media.

Our findings highlight that connected WeChat accounts exhibit a distinctly more favorable tone immediately after negative traditional media coverage, effectively counteracting potential damage to firm reputation and market value. This approach is especially pronounced in firms with high incentives to stabilize their stock prices and where executive career concerns are elevated, such as during acquisition periods or among firms with considerable insider ownership or volatile stock prices. Through this mechanism, corporations can manage and temper public perception and sentiment, emphasizing social media's role as a contemporary tool for real-time reputation management.

While this study makes a novel contribution to the literature on social media and corporate media management, several limitations remain. The primary limitation is its focus on Chinese firms, which may limit the generalizability of the findings to other markets with distinct regulatory environments, media landscapes, or social media usage patterns. In countries where media regulations differ, corporate use of media connections could manifest differently, and future studies might benefit from comparative analyses across countries.

Additionally, while we find that the tone in connected media becomes more positive post-event, this study does not fully address the long-term efficacy of such reputation management tactics. Future research could expand on these insights by examining whether these positive narratives ultimately lead to sustained improvements in firm valuation, investor confidence, or customer loyalty, or if they provide only short-term stabilization. Another worthwhile extension would be investigating the underlying mechanisms and costs associated with establishing and maintaining these media connections, especially in cases where connections may entail implicit or explicit bias risks.

Future studies could also explore how investors and regulators interpret firms' use of social media to counter negative news, potentially investigating whether repeated or highly visible corporate interventions in social media might signal transparency concerns to the market or attract regulatory scrutiny. Lastly, exploring additional media platforms, particularly in cross-market comparisons, could provide deeper insights into how social media ties shape firm strategies in different cultural, economic, and regulatory settings. As the media continues to evolve, understanding the broader implications of corporate influence on public narratives will be increasingly important for stakeholders across finance, governance, and media ethics.

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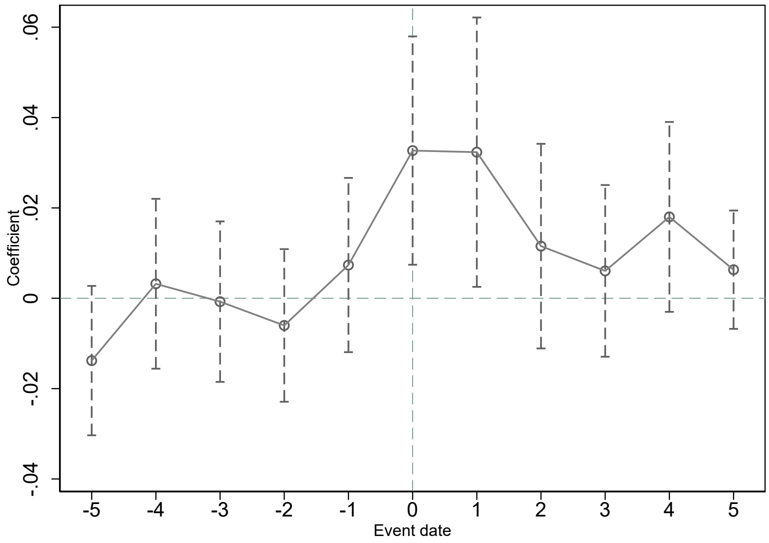
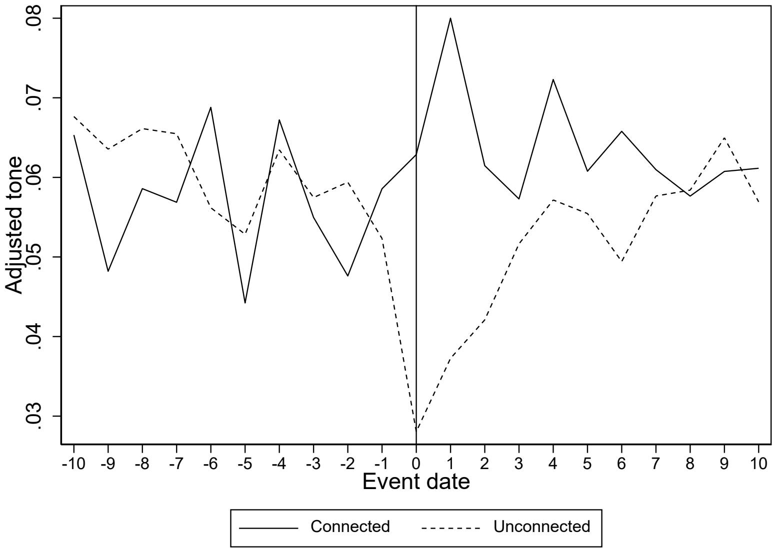
Figure 1. Parallel trends

This figure presents the results of the parallel trends analyses. Panel A illustrates the estimated coefficients for the interaction between *Connect* and relative event time dummies in the model from Column 2 of Table 3, with 95% confidence intervals represented by dashed lines. Panel B displays the daily relatedness-adjusted tone scores over the [-10, +10] event window for both connected WeChat articles (solid line) and unconnected WeChat articles (dashed line).



Panel A. Dynamic DiD



Panel B. Daily average tone score over the event window

Figure 2. In-space placebo test

This figure displays the histogram distribution of the estimated coefficients for *Connect* × *Post* from a placebo test. In this test, we repeat our baseline regression specified in Eq. (1) 500 times, randomly assigning a value of one to the *Connect* indicator while keeping the proportion of connected articles consistent with the actual sample.

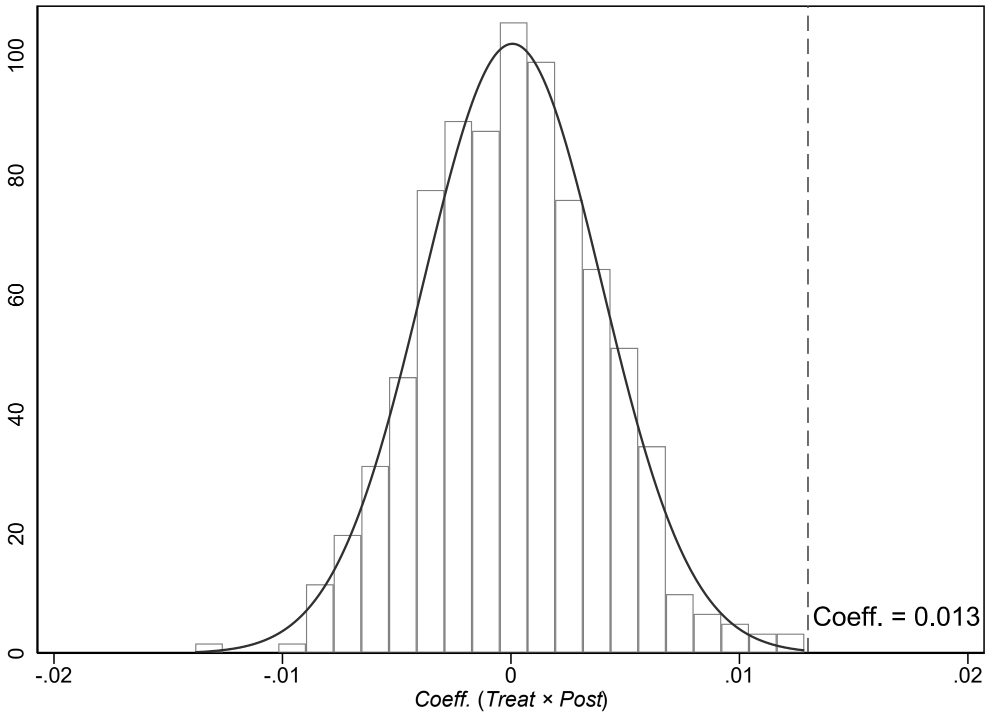


Table 1. Pervasiveness of social media connection

This table presents the distribution of our sample firms with a social media connection over the entire sample period, spanning from 2016 to July 31, 2023, and across individual years within this period. The sample covers 4,978 firms with at least one WeChat article. For the full sample and each calendar year, we present the number of connected firms, the total number of sample firms, the percentage of connected firms, and the market capitalization of connected firms as a percentage of the total market capitalization of all sample firms.

	# of connected firms	*# All sample firms*	*% of connected firms*	*% total market cap*
2016-2023 (full sample)	730	4,978	14.66%	-
2016	208	2,612	7.96%	20.36%
2017	251	2,877	8.72%	24.40%
2018	299	3,308	9.04%	27.10%
2019	373	3,548	10.51%	32.99%
2020	443	3,733	11.87%	29.07%
2021	552	4,088	13.50%	28.02%
2022	652	4,566	14.28%	30.79%
2023	729	4,874	14.96%	33.91%

Table 2. Summary statistics

This table presents summary statistics for articles published around the event day and the social media connection indicator used in our baseline regression. The sample includes 286 events of extremely poor traditional media coverage from 2016 to July 2023, comprising 2,019 traditional news articles published on the event date and 25,580 WeChat articles published within the [-10, +10] event window. Section 2.3 details the event identification process. Panel A reports statistics for traditional news articles published on the event day. Panel B focuses on WeChat articles published over the [-10, +10] event window. Panel C provides statistics for the *Connect* indicator. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A1 presents the descriptions of these variables in detail.

	N	Mean	St.Dev.	Min.	Median	Max.
Panel A. Characteristics of traditional news articles						
# of traditional news articles	286	7.060	8.650	1	4	67
Traditional news tone [0]	2,019	-0.137	0.356	-0.991	0.005	0.983
Panel B. Characteristics of WeChat news articles						
# of WeChat articles [-10, +10]	286	91.878	100.370	4	54	565
# of connected WeChat articles [-10, +10]	286	13.836	24.259	2	4	124
# of connected WeChat articles [-10, -1]	286	6.406	11.666	1	2	67
# of connected WeChat articles [0, +10]	286	7.430	12.898	1	2	59
# of unconnected WeChat articles [-10, +10]	286	78.042	89.970	2	48	473
# of unconnected WeChat articles [-10, -1]	286	35.154	40.014	1	23	288
# of unconnected WeChat articles [0, +10]	286	42.888	54.575	1	26	434
WeChat tone	25,580	0.055	0.121	-0.299	0.026	0.593
Panel C. Social media connection						
Connect	25,580	0.138	0.345	0.000	0.000	1.000

Table 3. Whether firms counteract negative traditional news coverage using social media

Column 1 of this table performs baseline difference-in-difference analyses to examine how connected social media outlets react to events with extremely negative traditional media coverage. The sample consists of 286 events over the period 2016 to July 2023, covering 25,580 WeChat articles around the [-10, +10] window. The dependent variable is *WeChat tone*, where a greater value indicates a more positive WeChat tone. *Connect* is an indicator variable that equals to one if the firm has established a social media connection in the previous year, and zero otherwise. *Post* is an indicator variable that equals to one if the article was published over the [0, +10] window, and zero otherwise. We control for year-month, event, relative-date-to event (or event date), and WeChat fixed effects, as well as cluster standard deviations at the event level. Section 2.3 discusses how we identify these negative events in detail. Column 2 presents a placebo test using 234 events with extremely positive traditional media coverage, constructed symmetrically to the baseline sample. Appendix Table A1 discusses how we construct variables in detail. *P*-values are reported in parentheses. *, **, and *** denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

	Negative news events	Positive news events
Dep. Var.= *WeChat tone*	(1)	(2)
Connect* × *Post	0.013***	0.006
	(0.005)	(0.007)
Connect	-0.010	0.022
	(0.009)	(0.015)
Observations	25,580	11,595
R-squared	0.225	0.237
Year-month FEs	Yes	Yes
Event FEs	Yes	Yes
Event date FEs	Yes	Yes
Wechat FEs	Yes	Yes
Cluster by event	Yes	Yes

Table 4. Robustness

This table presents robustness checks to validate the baseline results from Column 1 of Table 3. Panel A conducts in-time placebo tests by shifting the treatment period from one to five period backward. Following conventions, we exclude post-event observations in the original sample. Panel B applies alternative event identification strategies: identifying events where the daily average traditional media tone is in the bottom quartile of the day (Column 1), in the bottom decile across all days in the sample period (Column 2), or below the previous year's average tone by more than one standard deviation (Column 3). Panel C examines alternative event windows ([-5, +5] and [-20, +20]) and minimum lag days between events (20 or 30 days). Panel D relaxes the event criteria by allowing non-missing connected articles in the pre-event window (Column 1) and imposes stricter controls using relative-date-to-event fixed effects (Column 2). Parallel trend test results for these robustness checks are shown in Appendix Figure A4. *P*-values are in parentheses, and ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. In-time placebo tests (restricted to the pre-treatment sample)

Dep. Var.= *WeChat tone*	(1)	(2)	(3)	(4)	(5)
Shifting the treatment time X-period backward	X=1	X=2	X=3	X=4	X=5
Connect* × *Post	**0.007**	**0.002**	**0.002**	**0.004**	**-0.001**
	(0.010)	**(0.007)**	**(0.006)**	**(0.005)**	**(0.005)**
Connect	-0.002	-0.001	-0.002	-0.003	-0.000
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Observations	11,374	11,374	11,374	11,374	11,374
R-squared	0.278	0.278	0.278	0.278	0.278
Year-month FEs	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes
Event date FEs	Yes	Yes	Yes	Yes	Yes
WeChat FEs	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes

Panel B. Alternative event identification strategies

Dep. Var.= *WeChat tone*	(1)	(2)	(3)
	Bottom quartile	Bottom 10% in all sample	Previous year mean & std.
Connect* × *Post	**0.012*****	**0.029*****	**0.029*****
	(0.004)	**(0.007)**	**(0.007)**
Connect	-0.001	-0.006	-0.004
	(0.004)	(0.015)	(0.015)
Observations	64,774	13,032	13,714
R-squared	0.198	0.266	0.262
Year-month FEs	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes
Event date FEs	Yes	Yes	Yes
WeChat FEs	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes

Table 4. Robustness (cont.)

Panel C. Alternative event windows or alternative minimum lag days between events

Dep. Var.= *WeChat tone*	(1) [-5, +5]	(2) [-20, +20]	(3) 20 days	(4) 30 days
Connect × Post	**0.025*****	**0.008***	**0.016*****	**0.016****
	(0.008)	**(0.004)**	**(0.006)**	**(0.006)**
Connect	-0.027	0.002	-0.011	-0.013
	(0.017)	(0.006)	(0.010)	(0.011)
Observations	10,609	67,397	23,342	20,543
R-squared	0.243	0.189	0.222	0.222
Year-month FEs	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes
Event date FEs	Yes	Yes	Yes	Yes
WeChat FEs	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes

Panel D. Non-missing post-window articles only or stricter fixed effects

Dep. Var.= *WeChat tone*	(1) *Non-missing post-window articles only*	(2) *Stricter fixed effects*
Connect × Post	**0.016*****	**0.018****
	(0.005)	**(0.009)**
Connect	-0.007	-0.018***
	(0.007)	(0.005)
Observations	39,111	25,112
R-squared	0.244	0.256
Year-month FEs	Yes	No
Event FEs	Yes	No
Event date FEs	Yes	No
WeChat FEs	Yes	Yes
Event-Event date FEs	No	Yes
Cluster by event	Yes	Yes

Table 5. Stock market reactions to positive social media narratives

This table presents an event-study analysis at the firm-day level to examine how the stock market responds to connected WeChat coverage following negative news events. The analysis focuses on the post-event window [0, +10] for the 286 events identified in Section 2.3. The dependent variables are the daily abnormal return (*AR*), defined as the firm's raw return minus the value-weighted market return (Columns 1 and 4), and the cumulative abnormal returns (*CAR*) over the [0, +1] and [0, +2] windows (Columns 2–3 and 5–6). The main independent variable, *Connected day*, is an indicator variable that equals one if at least one article from a connected WeChat account is published for the firm on that day, and zero otherwise. Firm-days with no WeChat articles are excluded from the sample. Columns 1–3 include firm and year-month fixed effects with standard errors clustered at the firm level; Columns 4–6 include event and year-month fixed effects with standard errors clustered at the event level. *P*-values are reported in parentheses. *, **, and *** denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. =	AR [0]	CAR [0, +1]	CAR [0, +2]	AR [0]	CAR [0, +1]	CAR [0, +2]
Connected day	**0.003*** **	**0.005*** **	**0.006*** **	0.002	**0.004** **	**0.004** **
	(0.001)	**(0.002)**	**(0.002)**	(0.001)	**(0.001)**	**(0.002)**
Constant	-0.002***	-0.002***	-0.003***	-0.002***	-0.001**	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	2,364	2,364	2,364	2,363	2,363	2,363
R-squared	0.176	0.223	0.250	0.324	0.394	0.424
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	No	No	No
Cluster by firm	Yes	Yes	Yes	No	No	No
Event FEs	No	No	No	Yes	Yes	Yes
Cluster by event	No	No	No	Yes	Yes	Yes

Table 6. How firms counteract negative traditional news coverage using social media

This table investigates how connected firms respond to negative traditional media coverage by examining article topics/labels. Panel A presents the topic distribution for traditional articles published on the event date, as well as unconnected and connected WeChat articles published within the [0, +10] event window. For each article-firm pair, we focus on the topic identified by AI as most relevant to the focal firm, with detailed definitions of topic types provided in Section 4. Panel B further examines whether connected WeChat articles are more likely to cover topics differing from event-date traditional news articles, compared to unconnected WeChat articles. The dependent variable, *Same label*, is an indicator equal to one if label of the WeChat article matches the most frequently mentioned label in traditional media articles on the event date, and zero otherwise. The main independent variable, *Connect*, is an indicator equal to one if the firm is connected to at least one WeChat firm in the previous year, and zero otherwise. In Column 1, we do not add any control. In Column 2, we cluster standard deviations at the event level. In Column 3, we further control for year-month, event, event date (i.e., relative-to-event-date), and WeChat fixed effects. *P*-values are reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Topic distribution

	Traditional articles [0]		Unconnected WeChat articles [0,10]		Connected WeChat articles [0,10]	
Topic types	N	%	N	%	N	%
Market assessment and ratings	302	**23.09**	2,944	**29.79**	133	7.66
Financial performance	246	**18.81**	1,223	**12.37**	61	3.51
Industry policies and macro-environment	155	**11.85**	2,037	**20.61**	456	**26.25**
Negative events	141	10.78	357	3.61	3	0.17
Equity structure	131	10.02	318	3.22	2	0.12
Investment/financing activities	114	8.72	1076	10.89	152	8.75
Production and sales activities	106	8.10	871	8.81	124	7.14
R&D, innovation, and human resources	68	5.20	534	5.40	564	**32.47**
Strategy, cooperation, and CSR	45	3.44	524	5.30	242	**13.93**
Total	1,308	100	9,884	100	1,737	100

Panel B. Regression analyses

Dep. Var. = *Same label*	(1)	(2)	(3)
Connect	**-0.151*****	**-0.151*****	**-0.118*****
	(0.007)	**(0.024)**	**(0.022)**
Observations	20,210	20,210	20,209
R-squared	0.015	0.015	0.212
Year-month FEs	No	No	Yes
Event FEs	No	No	Yes
Event date FEs	No	No	Yes
Cluster by event	No	Yes	Yes

Table 7. Incentives of counteracting negative traditional news coverage using social media

This table employs subsample analyses to examine whether firms with social media connections are more likely to leverage their connections to counteract negative traditional news coverage, particularly when managers have greater incentives to stabilize stock price (Panel A) or have greater career concerns (Panel B). The regressions follow the model specified in Eq. (1). To assess stock price stabilization incentives, we consider whether the firm is going to announce an acquisition within the next three months, or where the interests of large shareholders or management are closely linked to market performance. We define shareholder interests as closely linked to market performance when the largest shareholder's ownership stake is in the top tercile across sample firms or if the ultimate controller has pledged shares. Management interests are defined as closely linked to market performance if management ownership is in the top tercile or if the management team holds stock options. To capture managerial career concerns, we use three proxies: 1) poor operating performance, defined as firms in the bottom tercile of ROA within their industry in the previous year; 2) large stock price volatility, defined as firms in the top tercile of stock price volatility in the previous year; and 3) short CEO tenure, defined as CEOs with less than two years in their role at the start of the year. *P*-values are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Stock price stabilization

Dep. Var.= *WeChat tone*	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	Acquisition within the next three months		Large shareholder interests closely linked to market performance		Management interests closely linked to market performance	
	Yes	No	Yes	No	Yes	No
Connect* × *Post	**0.059****	**0.013****	**0.027****	**0.011***	**0.022*****	**0.0004**
	(0.025)	**(0.005)**	**(0.010)**	**(0.006)**	**(0.007)**	**(0.007)**
Connect	-0.021	-0.005	-0.044***	0.001	-0.026	0.027**
	(0.050)	(0.009)	(0.017)	(0.010)	(0.016)	(0.013)
P*-value Diff. in *Connect* × *Post	**0.010**		**<0.001**		**0.040**	
Observations	703	24,726	7,254	18,040	13,072	12,243
R-squared	0.452	0.228	0.307	0.227	0.250	0.256
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event date FEs	Yes	Yes	Yes	Yes	Yes	Yes
WeChat FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Incentives of counteracting negative traditional news coverage using social media (cont.)

Panel B. Managerial career concern

Dep. Var.= *WeChat tone*	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	Poor operating performance		High stock price volatility		Short CEO tenure	
	Yes	No	Yes	No	Yes	No
Connect* × *Post	**0.050*****	**0.011***	**0.017****	**0.008**	**0.018***	**0.006**
	(0.016)	**(0.006)**	**(0.007)**	**(0.008)**	**(0.010)**	**(0.007)**
Connect	-0.041	-0.015	-0.039**	-0.002	-0.007	-0.002
	(0.027)	(0.010)	(0.016)	(0.010)	(0.021)	(0.011)
P*-value Diff. in *Connect* × *Post	**<0.001**		0.100		**0.090**	
Observations	2,528	21,564	10,736	13,322	6,890	15,695
R-squared	0.432	0.219	0.261	0.261	0.267	0.246
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event date FEs	Yes	Yes	Yes	Yes	Yes	Yes
WeChat FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Effectiveness of social media connections

This table conducts firm-year level analyses to investigate the effectiveness of social media connections. Specifically, we examine whether firms with social media connections differ from unconnected firms in acquisition market reactions (Panel A), insider trading profits (Panel B), and CEO/Chairman turnover (Panel C). In Panel A, the dependent variable is *CAR [-1, +1]*, the standardized CAPM-based cumulative abnormal returns over the [-1, 1] merger window. In Panel B, the dependent variable is insider trading profits *Ln (1+Insider profits)*, defined as the 6-month (or 12-month) annualized return calculated by comparing the stock price exactly 6 (or 12) months after the trade with the insider transaction price (Columns 1–2). For robustness, we also use the average price over the subsequent 6 or 12 months to mitigate potential bias from daily price fluctuations (Columns 3–4). In Panel C, the dependent variable is a dummy variable indicating CEO/Chairman turnover within the next 2 or 3 years. The main independent variable, *Connect*, is an indicator equal to one if the firm is connected to at least one WeChat firm in the previous year, and zero otherwise. Definitions of control variables are provided in Appendix Table A1. In all specifications, we control for firm and year fixed effects, as well as cluster standard deviations at the firm level. *P*-values are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Acquisition market reaction

	(1) *CAR* [-1, +1]	(2) *CAR* [-1, +1]	(3) *CAR* [-1, +1]
Connect	**0.016****	**0.015****	**0.015*****
	(0.007)	**(0.007)**	**(0.006)**
Firm size	-0.013***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)
Firm age	0.004	0.004	0.005
	(0.005)	(0.005)	(0.005)
B/M	0.014*	0.015**	0.014*
	(0.008)	(0.008)	(0.008)
ROA	-0.032*	-0.032*	-0.031*
	(0.018)	(0.018)	(0.019)
Leverage	0.028***	0.025***	0.023**
	(0.009)	(0.009)	(0.009)
BHAR	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.002)
Volatility	0.090*	0.096**	0.082*
	(0.048)	(0.048)	(0.049)
Turnover	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Institutional ownership	0.003	0.006	0.004
	(0.013)	(0.013)	(0.013)
SOE	0.003	0.003	0.004
	(0.006)	(0.005)	(0.005)
Observations	9,463	9,463	9,463
R-squared	0.299	0.304	0.323
Deal characteristics	No	Yes	Yes
Year FEs	Yes	Yes	No
Year-month FEs	No	No	Yes
Firm FEs	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes

Table 8. Effectiveness of social media connections (cont.)

Panel B. Insider trading

Dep. Var. = Ln (1+*Insider profits*)	(1) six-month	(2) 12-month	(3) six-month (Avg. price)	(4) 12-month (Avg. price)
Connect	**0.655****	**0.866*****	**0.739****	**0.912*****
	(0.301)	**(0.309)**	**(0.291)**	**(0.292)**
Firm size	1.368***	1.314***	1.260***	1.188***
	(0.168)	(0.168)	(0.165)	(0.160)
Firm age	-0.029	-1.234***	-0.026	-1.159***
	(0.245)	(0.238)	(0.238)	(0.231)
B/M	-3.204***	-3.474***	-3.010***	-3.029***
	(0.460)	(0.456)	(0.447)	(0.437)
ROA	-1.076	0.225	-1.117	-0.014
	(0.781)	(0.792)	(0.775)	(0.763)
Leverage	-1.675***	-1.632***	-1.471***	-1.315**
	(0.548)	(0.555)	(0.544)	(0.532)
BHAR	0.802***	1.118***	0.752***	1.028***
	(0.116)	(0.113)	(0.112)	(0.110)
Volatility	-8.529***	-14.937***	-9.257***	-12.297***
	(2.567)	(2.584)	(2.474)	(2.541)
Turnover	-0.221***	-0.248***	-0.168***	-0.238***
	(0.046)	(0.045)	(0.045)	(0.044)
Institutional ownership	1.579	1.887*	1.311	1.705*
	(1.068)	(1.047)	(1.034)	(1.000)
SOE	-0.762**	-1.243***	-0.698**	-1.136***
	(0.363)	(0.337)	(0.347)	(0.329)
Observations	22,594	23,019	22,550	23,070
R-squared	0.453	0.472	0.451	0.472
Year FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes

Table 8. Effectiveness of social media connections (cont.)

Panel C. CEO/Chairman turnover

	(1)	(2)
Dep. Var. =	CEO/Chairman turnover over the next two years	CEO/Chairman turnover over the next three years
Connect	**-0.043***	**-0.052****
	(0.024)	**(0.026)**
Firm size	0.007	0.025**
	(0.011)	(0.012)
Firm age	0.104***	0.151***
	(0.015)	(0.017)
B/M	0.065**	0.076**
	(0.029)	(0.032)
ROA	-0.224***	-0.213***
	(0.052)	(0.050)
Leverage	0.023	-0.016
	(0.038)	(0.040)
BHAR	-0.001	0.001
	(0.006)	(0.006)
Volatility	0.337**	0.304**
	(0.141)	(0.141)
Turnover	0.005*	0.006**
	(0.003)	(0.003)
Institutional ownership	-0.092*	-0.082
	(0.053)	(0.057)
SOE	0.066**	0.055**
	(0.026)	(0.028)
Observations	29,249	29,249
R-squared	0.358	0.483
Year FEs	Yes	Yes
Firm FEs	Yes	Yes
Cluster by firm	Yes	Yes

Appendix

Figure A1. Examples of WeChat official account

Panel A. 36Kr

Official Accounts

36氪

36氪是服务中国新经济参与者的卓越品牌和开创性平台，提供新锐深度的商业报道，强调趋势和价值，我们的slogan是：让一部分人先看到未来。

收起

拼多多Temu三季度放缓显著，租用菜鸟香港eHub完善基建 | 独家

李小霞 · 2024年11月28日 19:26

被寄予厚望的半托管，没有想象中好做。

拼多多 股权融资 上海市 2014-01

专注拼团的社交电商平台

36氪报道 消费电商 独角兽 高新技术企业 WISE2024年度企业榜单-跨境服务

我要联系

文 | 李小霞

编辑 | 乔芊 杨轩

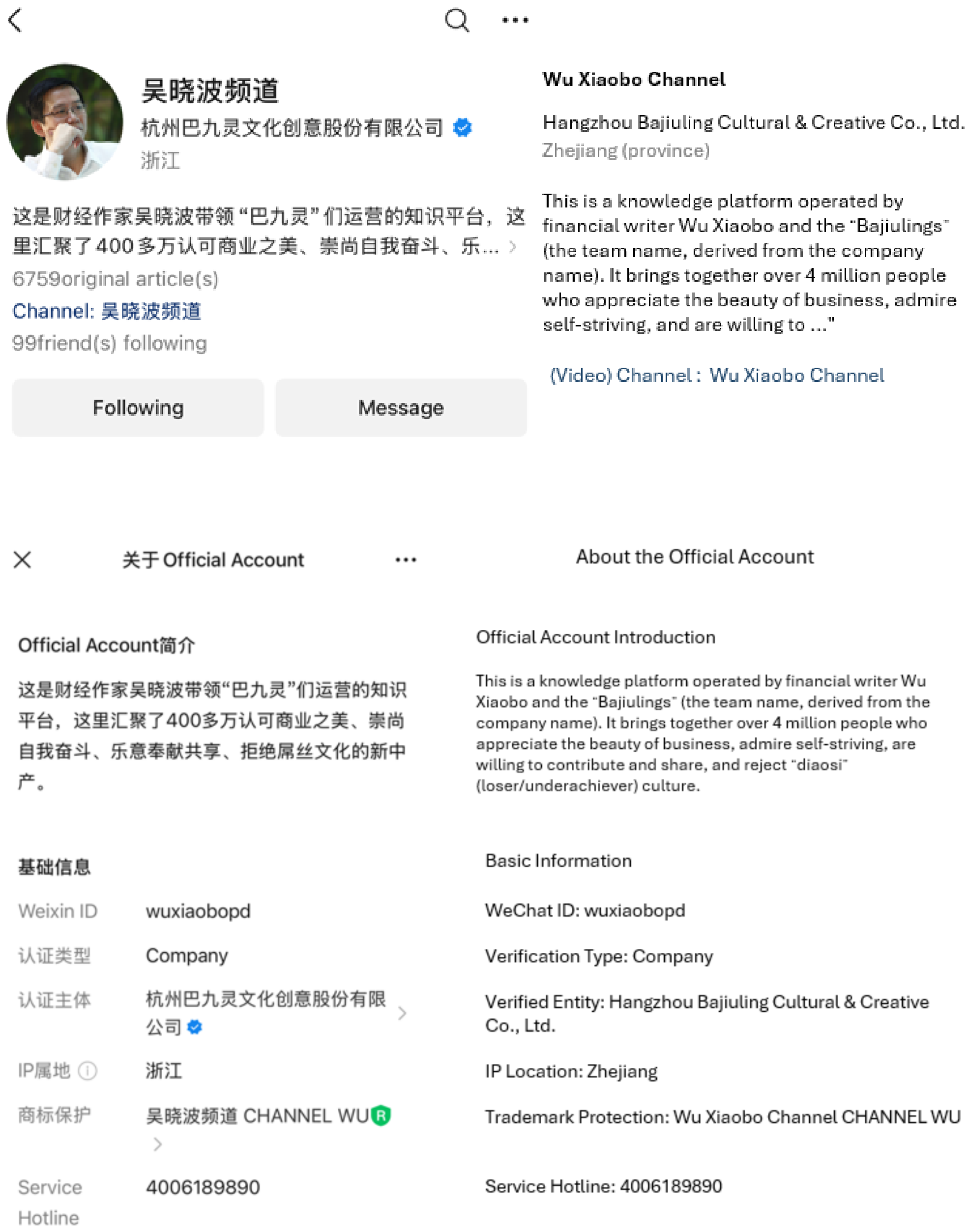
拼多多一直狂奔的海外业务开始明显慢了下来。

在拼多多最新季报里，包含Temu在内的交易服务营收为500亿元，增速由上季度的234%降到72%，且比市场预期低了30亿。据海豚投研分析，不到预期主要源于拼多多主站降低技术服务费、退货返还佣金等举措，冲减了主站的佣金收入。

The figure presents screenshots from *36Kr* (WeChat account: wow36kr), one of the most influential WeChat official accounts in the business domain in China. Launched in 2017, 36Kr offers news and analysis on business and finance and has grown to over five million followers. The top part displays its official introduction, which states: *"36Kr is a leading brand and pioneering platform serving participants in China's new economy. We provide cutting-edge and in-depth business reporting, emphasizing trends and value. Our slogan is: Let some people see the future first."* The bottom part shows a representative article published in November 2024, titled *"Pinduoduo's Temu Shows Significant Slowdown in Q3, Leases Cainiao's Hong Kong eHub to Improve Infrastructure | Exclusive."*

Figure A1. Examples of WeChat official account (cont.)

Panel B. Wu Xiaobo Channel



This figure present screenshots from *Wu Xiaobo Channel* (WeChat account: *wuxiaobopd*), one of China's earliest and most popular WeChat official accounts specializing in business commentary, corporate history, and economic trends. Launched in 2014 by influential author Wu Xiaobo, the account had amassed over four million subscribers and published more than 6,700 original articles as of July 2025.

Figure A2. Examples of WeChat account – public firm connection

Panel A. Wu Xiaobo Channel and Wufangzhai

Wu Xiaobo Channel

Hangzhou Bajiuling Cultural & Creative Co., Ltd.
Zhejiang (province)

This is a knowledge platform operated by financial writer Wu Xiaobo and the "Bajiulings" (the team name, derived from the company name). It brings together over 4 million people who appreciate the beauty of business, admire self-striving, and are willing to ..."

(Video) Channel：Wu Xiaobo Channel

The screenshots illustrate that Wu Xiaobo Channel, operated by Hangzhou Bajiuling Cultural & Creative Co., Ltd., is one of China's earliest and most popular WeChat accounts dedicated to business commentary, corporate history, and economic trends. Wufangzhai (Zhejiang Wufangzhai Industry Co Ltd, SHA: 603237) is a publicly listed firm specializing in traditional rice products, particularly zongzi.

The two entities are connected through a shared independent director, Degui Guo, who joined the board of Wufangzhai as an independent director in August 2017 and was subsequently appointed to the board of Bajiuling in March 2018. Following our methodology, we define the connection as beginning in March 2018, when director concurrently served on both boards.

Search "Wufangzhai" within Wu Xiaobo Channel

Article Date: 2021/4/20
Title: "Foreign Brands Demystified, Domestic Brands Crowned: A Review of Nine Major 'New Domestic Goods' Events of the Year | Golden Goods Award"
Snippet: "Compiled by Bajiuling (WeChat Official Account: Wu Xiaobo Channel). The past year was the 'Year of New Domestic Goods.' The COVID-19 pandemic..."

Article Date: 2019/5/10
Title: "Good Sticky Rice is a Dime a Dozen, but a Great Zongzi is One in a Hundred | Hundred Artisans Collection"
Snippet: "For many years, Wufangzhai's zongzi have been a veteran in the field, but the ingredient selection and formula remain true to its traditional roots..."

Article Date: 2018/11/12
Title: "Let's Splurge on These 'New Domestic Goods' Again | New Artisans News"
Snippet: "Wufangzhai became a partner for the 5th World Internet Conference Wuzhen Summit in 2018, and at the 'Light of the Internet' expo..."

Article Date: 2018/10/22
Title: "The Palace Museum, Google, the Nasdaq Big Screen... What Other Friends Will We Meet? | New Artisans News"
Snippet: "Click the picture for details. Wufangzhai, founded in 1921, launched an 80s retro-style advertisement..."

Article Date: 2018/5/24
Title: "Japanese Scallops, Australian Wagyu, Malaysian Durian... All Wrapped into a Zongzi | Hundred Artisans Collection"
Snippet: "This includes five of Wufangzhai's most representative flavors, in addition to four salted duck eggs, offering great value for money..."

Figure A2. Examples of WeChat account – public firm connection (cont.)

Panel B. CRIC Real Estate Research and Taihe

CRIC Real Estate Research

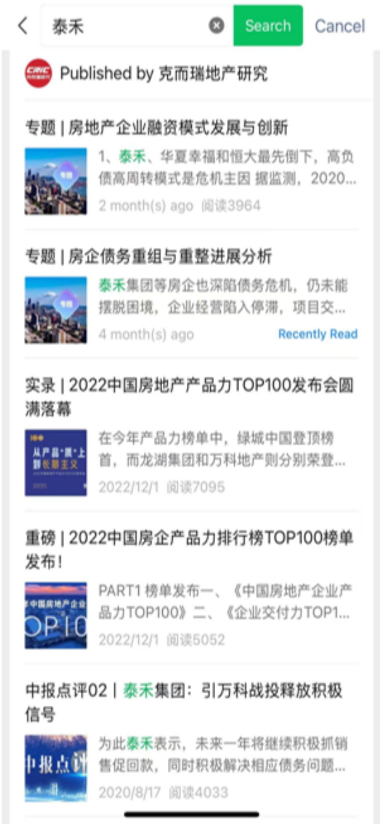
Shanghai CRIC Information Technology Co., Ltd.

Shanghai

Focusing on eight major research areas including the market and corporations, we specialize in the in-depth exploration of topics such as real estate market development, property developer operations, product strength of developers, diversification, and project management...

(Video) Channel : CRIC Real Estate Research

The screenshots illustrate that Taihe.co (Tahoe Group Co., Ltd., SZSE:000732, delisted in 2023) was a prominent Chinese real estate developer known for creating "Chinese-style luxury living" by integrating traditional Chinese architectural design with modern amenities. It held an ownership stake in Shanghai CRIC Information Technology Co., Ltd— the operator of CRIC Real Estate Research— from 2007 to 2018. Following our definition, the two entities are considered connected beginning in 2007.



Search "Taihe" within CRIC Real Estate Research

Published by CRIC Real Estate Research

Article Date: 2 month ago (as of July 2025)
Title: "Special Report | The Development and Innovation of Real Estate Enterprise Financing Models"
Snippet: "1. Taihe, China Fortune Land, and Evergrande were the first to fall; the high-debt, high-turnover model is the main cause of the crisis. According to monitoring, 2020..."

Article Date: 4 month ago (as of July 2025)
Title: "Special Report | Analysis of the Progress of Debt Restructuring and Reorganization at Real Estate Firms"
Snippet: "Taihe Group and other real estate firms are also deeply mired in a debt crisis and have not yet escaped their predicament. Business operations have stagnated, project deliveries..."

Article Date: 2022/12/1
Title: "Live Report | The 2022 China Real Estate Product Strength TOP 100 Launch Event Concludes Successfully"
Snippet: "In this year's Product Strength rankings, Greentown China took the top spot, while Longfor Group and Vanke Real Estate were also honored..."

Article Date: 2022/12/1
Title: "Blockbuster | The 2022 China Real Estate Developer Product Strength TOP 100 Rankings are Released!"
Snippet: "PART 1 Rankings Release: 1. 'China Real Estate Enterprise Product Strength TOP 100'; 2. 'Enterprise Delivery Capability TOP 1...'"

Article Date: 2020/8/17
Title: "Mid-Year Report Review 02 | Taihe Group: Bringing in Vanke as a Strategic Investor Sends a Positive Signal"
Snippet: "In response, Taihe stated that in the coming year it will continue to actively boost sales to promote cash collection, while also actively resolving its corresponding debt issues..."

Figure A3. An event example

This figure illustrates how connected firms may use social media to counteract negative traditional news coverage, based on the example of Taihe Group (stock ID 000732.SZ) who faced negative coverage from traditional news outlets on August 14, 2020.

Panel A. Example description in English

By connected WeChat firm (CRIC)

	Aug 14, 2020	Aug 15, 2020	Aug 16, 2020	Aug 17, 2020
Social media outlets		Guosheng Financial Control suspected of violating disclosure regulations; Taihe Group reports a net loss of over 1.5 billion yuan in the first half | Wind Risk Control Daily.	Too difficult! A near 1.6-billion-yuan loss in six months, with four bond defaults in one month, and nearly 40 billion yuan in principal and interest unpaid upon maturity.	**Mid-year Review 02 | Taihe Group: Bringing in Vanke as a strategic investor sends a positive signal.**
Traditional media outlets	Huge Loss! Taihe Group: Net profit for the first half of 2020 is approximately -1.582 billion yuan, down 201.33% year-on-year. Taihe Group's revenue in the first half of the year is 2.463 billion yuan, down 83% year-on-year, with a net loss of 1.582 billion yuan. Taihe Group: Revenue for the first half of 2020 is 2.463 billion yuan, down over 80% year-on-year. Taihe Group: Loss of 1.582 billion yuan in the first half, with provisions for liabilities and other penalties totaling approximately 776 million yuan. Taihe Group (000732.SZ): "17 Taihe 01" will not be able to repay principal and interest on time. Taihe Group reports a first-half loss of 1.582 billion yuan, previously announced that Vanke plans to invest 2.4 billion yuan | Hot Company. Financial Disclosure | Taihe Group reports a loss of 1.582 billion yuan in the first half, with an 80% drop in revenue. Announcement Analysis: Taihe Group reports a half-year loss of 1.582 billion yuan, shifting from profit to loss year-on-year. Taihe Group reports a first-half loss of 1.582 billion yuan; major shareholder plans to bring in Vanke as a strategic investor. Taihe Group: Net loss of 1.582 billion yuan in the first half of this year, compared to a profit of 1.561 billion yuan in the same period last year. Taihe Group: Net loss of 1.582 billion yuan in the first half of this year, compared to a profit of 1.561 billion yuan in the same period last year. Taihe Group: Debt defaults exceed 20 billion yuan. Taihe Group (000732.SZ): Shifted from profit to loss in the first half, with a net loss of 1.582 billion yuan. Taihe Group (000732.SZ): Shifted from profit to loss in the first half, with a net loss of 1.582 billion yuan. Taihe Group (SZ000732): Guaranteed party failed to fulfill repayment obligations, and the company has been listed as an enforced and discredited entity. Taihe Group reports a first-half loss exceeding 1.5 billion yuan, with only a few real estate projects delivering income. Taihe Group: Revenue for the first half of the year is 2.463 billion yuan | Mid-year Report Spotlight. Taihe Group: Cash inflow from financing exceeds 5 billion yuan in the first half. Taihe Group: Provides guarantees for wholly owned subsidiaries Fuzhou Taihe Jinxing and Suzhou Jinrun. Mid-year Report | Taihe Group: Revenue for the first half of the year is 2.463 billion yuan, with residential sales revenue of 1.806 billion yuan. Taihe Group 2020 mid-year board of directors' operational review. Taihe Group's stock price rose by 5% intraday on August 14.		Taihe Group reports a loss of 1.582 billion yuan in the first half of 2020 and has been sued over a financial loan contract dispute.	Original | Taihe's Debt Flood: First-half revenue of 2.5 billion yuan, insufficient to cover outstanding interest payments. Taihe Group: Rental and custodial income in the first half of the year was 187 million yuan, down 27.59% year-on-year. Taihe Group: Debt restructuring plan under development; whether Vanke can provide assistance remains uncertain. Taihe's revenue for the first half of the year is 2.463 billion yuan, with good sales for projects like Jinan Courtyard.

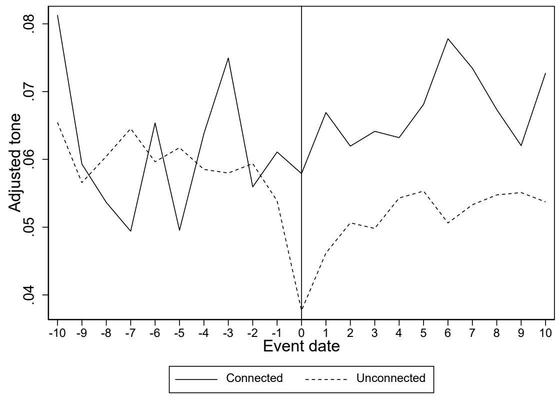
Figure A3. An example of event (cont.)

Panel B. Example description in original Chinese

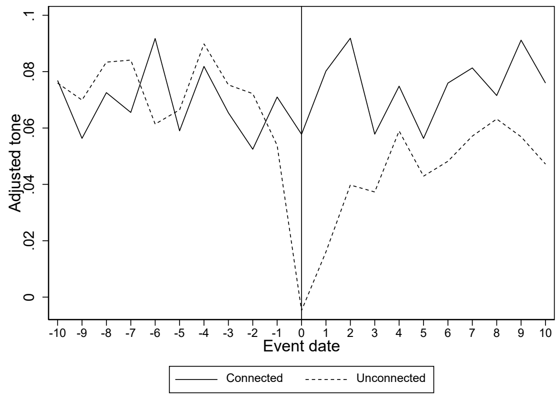
By connected WeChat firm (CRIC)

	Aug 14, 2020	Aug 15, 2020	Aug 16, 2020	Aug 17, 2020
Social media outlets		国盛金控涉嫌信披违规，泰禾集团上半年净亏损逾15亿元丨Wind风控日报	太难了！半年巨近16亿，一个月4笔债券违约，到期未还本息近400亿！	中报点评02丨泰禾集团：引万科战投释放积极信号
Traditional media outlets	巨亏！泰禾集团：2020年半年度净利润约-15.82亿元，同比下降201.33% 泰禾集团上半年营收24.63亿元同比减少83%，净亏15.82亿元 泰禾集团：2020年上半年营业收入24.63亿元 同比降超八成 泰禾集团：上半年亏损15.82亿元 计提负债并支付其他违约金等约7.76亿元 泰禾集团(000732.SZ)："17泰禾01"将无法按期兑付本息 泰禾集团上半年亏损15.82亿元，此前公告称万科拟24亿入股丨热公司 资色•曝年报丨泰禾集团上半年亏损15.82亿元 营收减8成 公告解读：泰禾集团半年度亏损15.82亿元 同比止盈转亏 泰禾集团上半年亏损15.82亿元 控股股东拟引万科为战投 泰禾集团：今年上半年净亏损15.82亿元 上年同期盈利15.61亿元 泰禾集团:2020中报净利润-15.82亿 同比下降201.35% 泰禾集团：债务违约金额超200亿 泰禾集团(000732.SZ)：上半年由盈转亏 净亏损15.82亿元 泰禾集团上半年营收24.63亿，同比降八成 泰禾集团(SZ000732)：被担保人未履行还款义务及公司被列为被执行人及失信被执行人 泰禾集团上半年亏损逾15亿元 仅有零星房产项目交付结转收入 泰禾集团：上半年营收24.63亿元 丨 半年报风云 泰禾集团：上半年筹资流入超50亿元 泰禾集团：为全资子公司福州泰禾锦兴、苏州锦润提供担保 半年报丨泰禾集团：上半年营业收入24.63亿元 住宅销售收入18.06亿元 泰禾集团2020年半年度董事会经营评述 泰禾集团8月14日盘中涨幅达5%		泰禾集团2020上半年亏损15.82亿元，且因金融借款合同纠纷被诉上法庭	原创 泰禾的债务洪流：上半年营收25亿，尚不足以覆盖拖欠利息 泰禾集团:上半年租金及托管收入1.87亿元,同比减少27.59% 泰禾集团：债务重组方案正在制定中 万科能否提供援助待定 泰禾上半年营收24.63亿 济南院子等项目销售良好

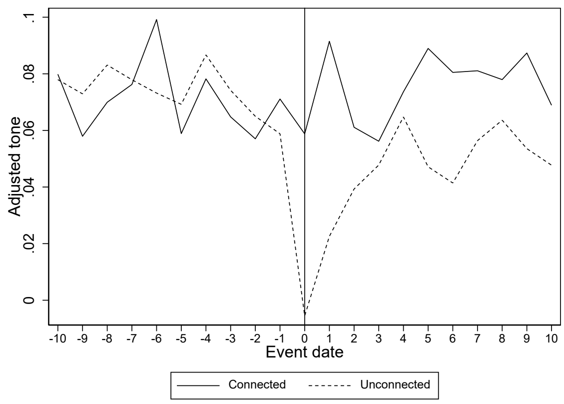
Figure A4. Parrel trends: robustness checks
This figure presents the daily average of relatedness-adjusted tone scores for connected and unconnected WeChat articles, corresponding to the robustness checks in Table 4. Each panel in the figure corresponds to a specific analysis in Table 4. The correspondence between each figure and the analyses in Table 4 is indicated by the figure titles.



Bottom quartile



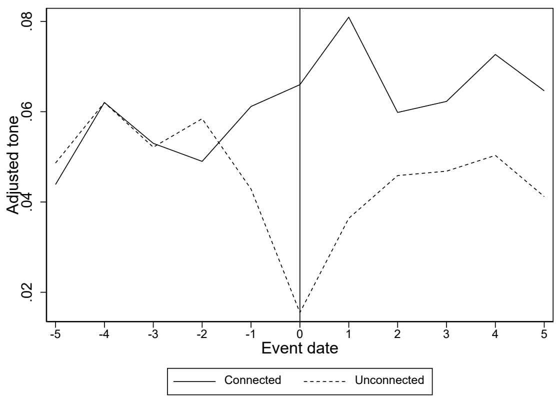
Bottom 10% in all sample



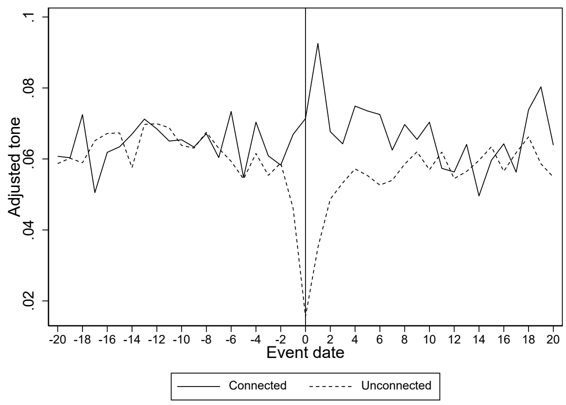
Previous year mean & std

Panel A. Alternative event identification strategies

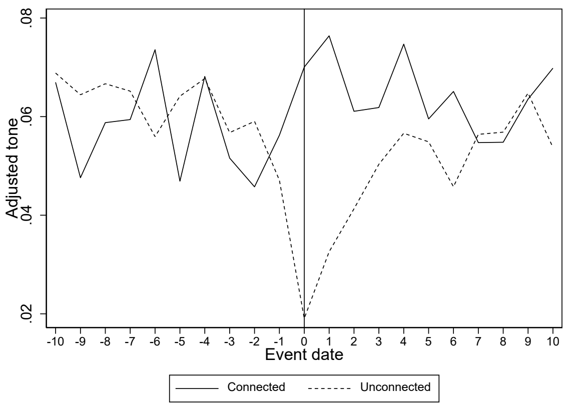
Figure A4. Parrel trends: robustness checks (cont.)



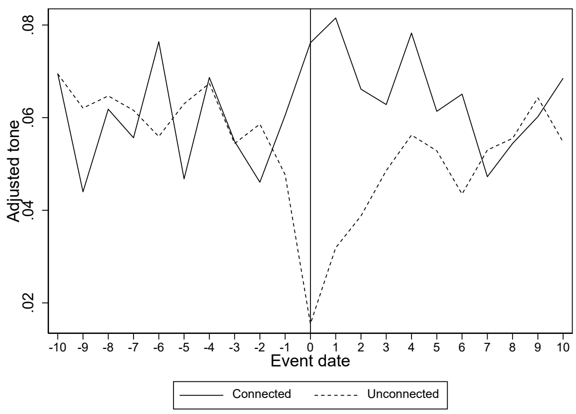
[-5, +5]



[-20, +20]

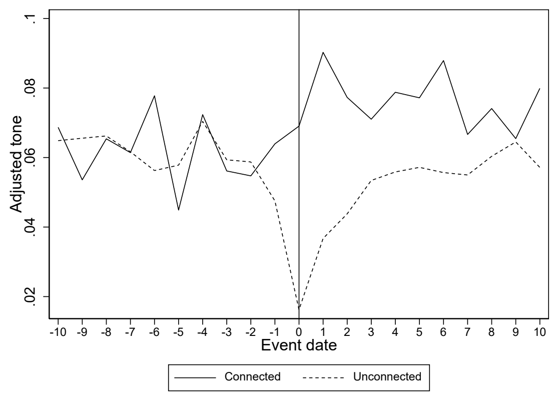


20 days



30 days

Panel B. Alternative event windows or Alternative minimum lag days between events



Panel C. Non-missing articles in the post-event window only

Table A1. Variable descriptions

Panel A. Social media connection	
Connect	An indicator variable that equals one if the firm has established a social media connection in the year. We assume that once established, the connection maintains its status till the end of the sample period.
Panel B. Media tone and attention	
WeChat tone	An article-level measure of WeChat sentiment score, measured as the product between the article sentiment score and the company relatedness score constructed by *Datayes*. The article sentiment score is a continuous variable ranging from the most negative tone (-1) to the most positive tone (+1). The company relatedness score is also a continuous variable, where a higher score indicates that the article discusses more exclusively about the focal firm.
Standardized WeChat tone	The difference between the tone of a WeChat article and the average tone of all sample WeChat articles over the prior calendar year, divided by the standard deviation of the tone of all sample WeChat articles over the prior calendar year.
Standardized tone difference	The difference between the *Standardized WeChat tone* (an article-firm level measure) and the *Standardized traditional news tone* (a firm-date level measure). In particular, *Standardized WeChat tone* is defined as above. *Standardized traditional news tone* is calculated as the difference between the daily average tone of all traditional news articles covering the firm and the average tone of all sample traditional news articles over the prior 3 months, divided by the standard deviation of the tone of all sample traditional news articles over the prior 3 months. For articles published in February (March) 2016, the calculation is based on the prior 1-month (2-month) data.
Panel C. Event short-term market reaction	
AR	Difference between the firm's daily raw return and value-weighted market return for all A-share stocks excluding those traded in the ChiNext or STAR markets.
CAR[0, 1]/ CAR[0, 2]	The cumulative abnormal return over the [0, +1]/ [0, 2] event window, where the benchmark is the value-weighted market return for all A-share stocks excluding those traded in the ChiNext or STAR markets.
Panel D. Baseline controls	
Firm size	The natural logarithm of total assets.
Firm age	The natural logarithm of one plus the number of years between the current year and the year of listing.
B/M	The book-to-market ratio, calculated as the book value of equity divided by the market value of equity.
ROA	Net income divided by total assets.
Leverage	Long-term debt divided by total assets.
BHAR	Annual buy-and-hold abnormal return, where the benchmark is the weighted average market portfolio.
Volatility	The standard deviation of weekly stock returns.
Turnover	Daily stock turnover ratio of the firm.
Institutional ownership	Percentage shares held by institutional shareholders.
SOE	An indicator variable that equals one if the firm is ultimately controlled by the government or a government-affiliated entity, and zero otherwise.

Table A1. Variable descriptions (cont.)

Panel D. Other variables	
Acquisition in the near future	An indicator variable that equals one if the firm is going to announce an acquisition within the next three months, and zero otherwise.
Large shareholder interests closely linked to market performance	An indicator variable that equals one if the percentage of shares held by the largest shareholder is in the top decile in the year or if the ultimate controller has pledged his/her shares, and zero otherwise.
Management interests closely linked to market performance	An indicator variable that equals one if the percentage of shares held by the top management team is in the top decile in the year, or if the top management team is granted with stock options, and zero otherwise.
Poor operating performance	An indicator variable that equals one if return on assets of the firm in the year is in the bottom tercile within the industry, and zero otherwise.
High stock price volatility	An indicator variable that equals one if stock return volatility of the firm in the year is in the bottom tercile within the industry, and zero otherwise.
Short CEO tenure	An indicator variable that equals one if CEO tenure is less than two years, and zero otherwise.
CAR [-1, +1]	The cumulative abnormal return over the [-1, +1] window of a merger, where the benchmark is the value-weighted market return for all A-share stocks excluding those traded in the ChiNext or STAR markets.
Insider profits	Insider trading profits as measured by Skaife, Veenman, and Wangerin (2013).
	An indicator variable that equals one if stock return volatility of the firm is in the bottom tercile within the industry, and zero otherwise.
CEO/Chairman turnover	An indicator variable that equals one if CEO or Chairman of the firm leaves their position over the next two or three years and does not return to the firm's CEO/Chairman list after departure. We do not consider the following situations as turnover: normal retirement, personal or health reasons, resignation, changes in controlling ownership, corporate governance restructuring, and CEO departures at the age of 65 or older.
Same label	An indicator variable that equals to one if label of the WeChat article matches the most frequently mentioned label in traditional media articles on the event date, and zero otherwise.

Table A2. The coverage of WeChat articles in *Datayes*

This table presents the market coverage of WeChat articles collected by *Datayes*. The sample consists of 1,254,529 articles issued by non-firm-official-accounts with a medium to high relatedness degree, covering 5,274 public firms over the period from January 2016 to July 2023. Market cap is calculated based on the last trading day of the fiscal year.

Year	% total market cap	% outstanding market cap
2016	98.63%	98.67%
2017	98.75%	98.72%
2018	98.75%	99.10%
2019	98.81%	99.18%
2020	99.15%	99.33%
2021	99.29%	99.33%
2022	99.29%	98.85%
2023 (as of July 31)	99.15%	98.63%

Table A3. The distribution of WeChat firms and social media connected firms by industry
Panel A (Panel B) of this table presents the distribution of our sample WeChat firms (public firms with a social media connection) by 1-digit CSRC industry.

Panel A. The industry distribution of WeChat firms

	1-digit Industry	# Connected WeChat firms	# All WeChat firms	% Connected/All
J	Financial Services	92	132	69.70%
L	Leasing and Business Services	40	169	23.67%
M	Scientific Research and Technical Services	32	144	22.22%
I	Information Transmission, Software, and Information Technology Services	26	125	20.80%
R	Culture, Sports, and Entertainment	12	92	13.04%
C	Manufacturing	8	9	88.89%
F	Wholesale and Retail Trade	6	19	31.58%
K	Real Estate	3	5	60.00%
G	Transportation, Warehousing, and Postal Services	2	3	66.67%
A	Agriculture, Forestry, Fishing, and Hunting	1	1	100.00%
B	Mining and Quarrying	1	1	100.00%
O	Residential Services	0	7	0.00%
N	Water, Environment, and Public Facilities Management	0	2	0.00%
P	Education	0	1	0.00%
	Total	**223**	**710**	**31.41%**

Panel B. The industry distribution of social media connected firms

1-digit industry		# Connected public firms	# All sample public firms	% Connected/All
J	Financial Services	86	129	66.67%
K	Real Estate	38	116	32.76%
G	Transportation, Warehousing, and Postal Services	36	110	32.73%
R	Culture, Sports, and Entertainment	20	65	30.77%
D	Electricity, Heat, Gas, and Water Production and Supply	39	133	29.32%
P	Education	3	12	25.00%
L	Leasing and Business Services	16	68	23.53%
Q	Health and Social Work	4	17	23.53%
H	Accommodation and Food Services	2	9	22.22%
F	Wholesale and Retail Trade	41	193	21.24%
E	Construction	18	109	16.51%
B	Mining and Quarrying	11	81	13.58%
I	Information Transmission, Software, and Information Technology Services	53	419	12.65%
A	Agriculture, Forestry, Fishing, and Hunting	6	48	12.50%
M	Scientific Research and Technical Services	12	103	11.65%
N	Water, Environment, and Public Facilities Management	10	94	10.64%
C	Manufacturing	334	3,256	10.26%
S	International Organizations and Others	1	15	6.67%
O	Residential Services	0	1	0.00%
Total		**730**	**4,978**	**14.66%**

Table A4. The selection model

This table performs linear probability regressions to examine what types of firms are more likely to have a social media connection. The dependent variable is $Connect_{2016\text{-}2023}$, an indicator variable that equals to one if the firm has ever established a social media connection over our sample period 2016-2023. In Column 1 (Column 2), we construct variables capturing firm characteristics based on the data in 2015 (in the year when the firm first came into our sample). In both regressions, we control for year and industry fixed effects, as well as cluster standard deviations at the firm level. Appendix Table A1 describes in detail variables employed in the table. *P*-values are reported in parentheses. *, **, and *** denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var: $Connect_{2016\text{-}2023}$	(1) Use characteristics in 2015 to predict later connection	(2) Use initial year characteristics to predict later connection
Firm size	**0.539*** **	**0.503*** **
	(0.079)	**(0.057)**
Firm age	**0.198** **	**0.131* **
	(0.093)	**(0.073)**
B/M	**-1.121*** **	**-1.064*** **
	(0.422)	**(0.343)**
ROA	1.055	0.377
	(1.071)	(0.796)
Leverage	0.254	0.161
	(0.360)	(0.292)
BHAR	**0.136** **	0.045
	(0.063)	(0.045)
Volatility	0.245	0.425
	(0.281)	(0.287)
Turnover	0.026	0.016
	(0.041)	(0.026)
Institutional ownership	-0.482	-0.274
	(0.718)	(0.503)
SOE	**0.883*** **	**0.803*** **
	(0.134)	**(0.109)**
Observations	2,600	4,977
Year FEs	No	Yes
Industry FEs	Yes	Yes
Cluster by firm	No	No

Table A5. Univariate analysis of financial characteristics: sample firms versus other firms
This table presents the results of univariate analyses comparing financial characteristics between the 54 sample firms and other public firms.

	Other firms		Connected firms		T-test	
	N	Mean	N	Mean	Diff.	p-value
Firm size	4885	21.310	54	22.650	-1.340	**0.000**
Firm age	4885	2.600	54	3.850	-1.250	**0.004**
B/M	4885	0.700	54	0.800	-0.090	**0.000**
ROA	4885	0.050	54	0.040	0.010	0.603
Leverage	4885	0.340	54	0.440	-0.100	**0.034**
BHAR	4885	0.550	54	0.270	0.280	0.124
Volatility	4885	0.090	54	0.080	0.020	**0.036**
Turnover	4885	2.570	54	1.190	1.390	**0.001**
InstOwn	4885	0.090	54	0.130	-0.040	**0.049**
SOE	4885	0.270	54	0.540	-0.260	**0.000**

Table A6. Definitions of article-firm news topic categories

We employ large language models (LLMs) to perform article-firm topic analyses. Specifically, for each article-firm pair, the LLM is tasked with summarizing the event relevant to the target firm and categorizing the summary into one of the predefined topics. This process enables consistent and detailed classification of events and activities associated with the target firms. The topics are defined as follows:

Categories	Contents
Financial performance	Financial reports, net profits, sales revenue, investment returns, cash inflows and outflows, and debt conditions (excluding bankruptcy, which falls under negative events).
Investment/financing activities	Asset transactions, restructuring, acquisitions, IPOs, capital raising activities, and changes in financing costs for activities completed, ongoing, or officially announced.
Production and sales activities	Inventory, raw materials, procurement, production costs, advertising expenditures, and supply chain operations.
Operating activities	Core business scope, operational conditions, and changes in core business operations, including expansions, adjustments, or modifications in activities related to the company's primary.
Equity structure	Equity changes, major shareholder pledges, dividends, and stock splits.
Market assessment and ratings	Stock price changes, analyst and investor evaluations (excluding major shareholders), and rating agency updates.
R&D, innovation, and human resources	Research and development activities, patents, senior management changes, key personnel updates, organizational restructuring, and recruitment.
Strategy, cooperation, and CSR	Corporate strategies, partnerships, CSR activities (e.g., environmental protection, donations), and public statements.
Negative events	Bankruptcy, legal disputes, regulatory warnings, trading suspensions, and public opinion crises.
Industry policies and Macro-environment	Industry trends, policy announcements, major events involving other companies, and macroeconomic analyses.