Connected Social Media

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

Abstract

We examine whether and how firms use connected social media outlets to counteract negative coverage in traditional media. Employing a sample of Chinese listed firms with ties to social media outlets, we find that connected outlets portray firms more favorably than unconnected ones. Following unfavorable coverage in traditional media, connected outlets shift attention toward long-term prospects and promote favorable narratives, consistent with an optimism-shifting mechanism. The effect is more pronounced when firms have stronger incentives to stabilize stock prices and when managers face heightened career concerns. Our findings highlight the role of connected social media outlets in shaping corporate narratives.

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

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[*] Jiang (Email: zhiqian.jiang@xmu.edu.cn) is associated with Xiamen University School of Management, No. 422 Siming South Road, Xiamen, Fujian, P. R. China, 361005. Liu (Email: baixiaoliu@phbs.pku.edu.cn) is associated with Peking University HSBC Business School, University Town, Nanshan District, Shenzhen, P. R. China, 518055. Xu (Email: yuchen.xu@unsw.edu.au) is associated with UNSW Business School, High Street, Kensington NSW 2052, Sydney, Australia. Zhang (Email: bohuizhang@cuhk.edu.cn) is associated with CUHK-Shenzhen School of Management and Economics and Shenzhen Finance Institute, 2001 Longxiang Boulevard, Longgang District, Shenzhen, P. R. China, 518172. We thank Anna Constantatos, Zhi Da, Shiyang Huang, Byoung-Hyoun Hwang, Fuwei Jiang, Zhiming Ma, Ronald Masulis, Gordon Phillips, 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) and Xu acknowledges the Young Scientists Fund of the National Natural Science Foundation of China (72203013) for financial support.

I. Introduction

Negative coverage in traditional media can impose substantial economic costs on firms. An extant body of research shows that negative media coverage can trigger regulatory intervention, reduce managerial compensation, and increase the likelihood of executive turnover (e.g., Dyck, Volchkova, and Zingales (2008), Liu, McConnell, and Xu (2017), Love, Lim, and Bednar (2017), and Baloria and Heese (2018)). Such costs make unfavorable traditional media coverage an important source of reputational and managerial pressure for firms. Firms, however, are not merely *passive recipients* of media coverage. Prior studies show that firms can actively influence media narratives through interactions with traditional media outlets, press releases, and strategic disclosure (e.g., Ahern and Sosyura (2014), Edmans, Goncalves-Pinto, Groen-Xu, and Wang (2018), and Ru, Xue, Zhang, and Zhou (2020)). The rise of social media has further expanded firms' ability to manage corporate narratives by providing rapid, widely accessible, and highly visible channels for reaching investors and other stakeholders.

Existing studies on firms' use of social media to shape corporate narratives focus primarily on channels directly controlled by firms such as official corporate social media accounts (e.g., Blankespoor, Miller, and White (2014), Jung, Naughton, Tahoun, and Wang (2018), and Blankespoor (2018)). Yet firms may also shape corporate narratives through an indirect channel: social media outlets that are not formally owned by the firm but are connected to the firm through ownership, investment, or personnel ties. Because these outlets appear as third-party intermediaries, their coverage may be perceived as less self-serving than direct corporate disclosure, making it potentially useful for proactive corporate narrative management during adverse events. Anecdotal evidence is consistent with the view that firms have strong incentives to manage unfavorable media exposure through indirect channels.[1]

[1] For example, a recent article in *The Economist* reports a "news extortion" case in China in which more than 180 firms preparing for public listings were threatened with damaging, often fabricated, claims on social media,

Little is known, however, about whether and how firms leverage connected social media outlets, or about the consequences and effectiveness of doing so.

In this study, we examine the role of connected social media outlets in shaping corporate responses to negative traditional media coverage. Specifically, we ask whether connected outlets portray firms more favorably than otherwise similar outlets, whether they become especially favorable following unfavorable traditional media coverage, and what incentives and consequences are associated with this form of indirect narrative management. To address these questions, 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, in China, traditional and social media differ sharply in their institutional constraints. Traditional media are highly regulated, and corporations face explicit restrictions on investing in or controlling news organizations. Social media, by contrast, is more commercially oriented and less clearly regulated. This contrast creates a setting in which firms may influence corporate narratives through social media connections even when direct control of traditional media is restricted.[2] 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 integrated application with many features (e.g., messaging, social media functionalities, e-commerce capabilities, and mobile payment services) and has accumulated over 1.3 billion monthly

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and some paid tens of thousands of yuan to suppress the coverage rather than report the scheme. See "News Extortion Is Rife in China", *The Economist*, June 18, 2026, https://www.economist.com/china/2026/06/18/news-extortion-is-rife-in-china (accessed July 16, 2026).

[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.

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. Internet Appendix Figure A1 presents two prominent examples—*36Kr* and *Wu Xiaobo Channel*—both of which focus 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 2016 to 2023, the database covers 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 define a public firm as connected to a social media outlet if the public firm directly holds shares in, or has shares held by, the entity operating the WeChat Official Account (the "WeChat firm"); if the public firm and the WeChat firm share key personnel, such as the ultimate controller, large shareholders, legal representatives, or members of the top management team; or if they share common ownership through 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.

Our empirical analyses begin by examining the determinants of firms' connections with social media outlets and whether firms with such connections are portrayed more positively across different information sources. We find that larger firms with stronger

[4] See Statista, "Number of Monthly Active WeChat Users", https://www.statista.com/statistics/255778/number-of-active-wechat-messenger-accounts/ (accessed July 16, 2026).

valuations are more likely to form connections, and that these connections are not driven by short-term responses to adverse media shocks. Coverage by connected outlets becomes more favorable following connection formation, and connected outlets exhibit a significantly more positive tone than unconnected outlets covering the same firm. This pattern is robust to controlling for firms' own disclosure activities. Our findings indicate a systematic corporate narrative advantage associated with social media connections.

Next, we examine whether firms with social media connections combat negative traditional news coverage via social media outlets. As our baseline analysis, we identify 286 firm-date events where the average tone of traditional news articles covering a firm falls in the bottom decile. 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) analysis, where the first difference compares pre- and post-event windows, and the second difference distinguishes articles published by social media outlets 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, with the effect concentrated in the post-event period. This pattern is robust to alternative, less restrictive sample constructions, and is absent in placebo tests based on positive news events. To further validate these findings, we conduct a battery of robustness checks, including in-space and in-time placebo tests, alternative event definitions, variations in event windows and sample construction, stricter fixed effects, and controls for firms' disclosures through alternative information channels. The estimated effects remain positive, statistically significant, and similar in economic magnitude.

We also examine whether the corporate narrative responses on social media outlets have real market consequences. We find that on days when firms are covered by at least one connected WeChat article following a negative news event, daily abnormal stock returns increase by approximately 0.3 percentage points relative to other days. These findings suggest that favorable narratives disseminated through connected outlets are associated with a partial mitigation of the adverse market reaction to negative news. This effect remains robust after controlling for firms' direct disclosure channels, indicating that third-party social media outlets play a distinct role beyond direct corporate communication.

Furthermore, we examine how firms with social media connections combat negative traditional news coverage through social media outlets. Using 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 short-term negative assessments of market reactions and financial performance. In contrast, connected WeChat accounts shift attention toward long-term firm development, including corporate strategy, R&D, cooperation, human resources, and CSR activities. This pattern is consistent with the "optimism shifting" mechanism in Cassella, Dim, and Karimli (2023). In particular, connected outlets do not primarily dispute unfavorable short-term information, but instead redirect attention toward more favorable, forward-looking aspects of the firm. In our setting, this optimism shifting operates through indirectly connected social media outlets rather than through firms' own disclosure channels. Consistent with this interpretation, the narrative management effect is concentrated in events involving soft information, where ambiguity leaves greater room for interpretation, and is absent for hard-information events grounded in fundamentals.

We also explore firms' incentives to counter negative traditional media coverage through social media. We find that our event study 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 shorter-tenured 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 executive turnover. The results indicate that through connections with social media outlets, firms can mitigate unfavorable traditional media coverage and protect managerial interests.

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) and Ang, Hsu, Tang, and Wu (2021)). A related strand of research considers social media as a firm-controlled disclosure channel. This literature typically focuses on official corporate accounts through which firms communicate directly with investors and other stakeholders. For example, Blankespoor et al. (2014) show that firms' use of Twitter to disseminate firm-initiated information can improve the firm's information environment. Jung et al. (2018) focus on firms' strategic choice of whether to disseminate earnings news through Twitter, showing that this choice varies with the nature of the news. Wolfskeil (2023), by contrast, examines how firms use official Twitter accounts around earnings announcements and shows that the timing, tone, and content of firm-initiated tweets affect information diffusion and investor responses. These studies view social media primarily as a direct channel through which firms disclose information, broaden dissemination, and communicate with market participants.

We add to this literature by studying a different channel: social media outlets that are *not formally owned* by firms but are connected to them through ownership, investment, or personnel ties. This distinction is important because connected outlets can appear to operate as third-party information intermediaries while producing narratives that are systematically more favorable to connected firms. Our evidence therefore extends the literature by showing that social media can serve not only as an independent source of market information or a direct disclosure channel, but also as an indirectly connected channel through which firms shape corporate narratives.

Second, we contribute to the literature on firms' proactive management of media coverage and corporate narratives. Prior studies show that firms are not passive recipients of media attention but can take actions to influence how they are covered and interpreted by the market. One strand of this literature examines how firms shape media coverage through direct communication and disclosure activities, such as press releases, investor relations, and strategic information releases (e.g., Bushee and Miller (2012), Ahern and Sosyura (2014), and Ru et al. (2020)). Another strand of literature studies how firms influence media incentives through economic or institutional relationships, including advertising, cross-holdings, political connections, and business ties with media organizations (e.g., Solomon

(2012), Gurun and Butler (2012), Xu (2024), Gurun (2020), Hossain and Javakhadze (2020), Yan, Wang, Wang, and Chan (2023), and He, Xia, Zhao, and Zuo (2025)). This literature emphasizes that corporate media coverage can reflect not only the information environment surrounding firms, but also firms' incentives and ability to shape that environment.

We extend this literature by examining connected social media outlets as a distinct channel of *indirect media management*. Unlike press releases, investor relations, or official corporate social media outlets, connected outlets are not direct corporate disclosure channels. Unlike traditional media organizations, they operate in a social media environment in which content can be produced and disseminated rapidly, widely, and with less clearly defined institutional boundaries. This setting allows firms to influence corporate narratives through outlets that appear to function as third-party information intermediaries while being connected to the firm through ownership, investment, or personnel ties. Our evidence shows that such connected outlets become especially favorable following negative traditional media coverage, suggesting that firms can use social media connections to counterbalance unfavorable media narratives and manage reputational shocks.

II. 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 this section. For definitions of all variables used, please refer to Internet Appendix Table A1.

A. 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.[5] Over the period from January 2016 to July 2023, *Datayes* collected over five million articles published by influential WeChat accounts.

Specifically, we focus on articles published by corporate-operated financial media accounts, excluding those from individuals, governments, or public firms' own official accounts. This design allows us to capture firm–social media connections that operate through ostensibly independent intermediaries rather than direct corporate communication. Our final sample includes approximately 700 WeChat accounts covering 5,274 public firms, representing 99.15% of the total market capitalization in China as of July 31, 2023 (Internet Appendix Table A2).[6] For simplicity, we refer to these corporate-operated WeChat entities as "WeChat firms" throughout the study. A public firm is considered "connected" if it is linked 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 person, such as an ultimate controller, shareholder, legal representative, or 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.

[5] "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.

[6] Our sample of approximately 700 WeChat firms is derived from an initial list of 3,543 accounts curated by *Datayes*, which 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; ii) government-operated accounts; and iii) individual-operated accounts, identified using *Qichacha* business registration data.

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 social media connections, Graph A of Internet 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. Graph B of Internet 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 that a 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]

Internet Appendix Table A3 provides a detailed breakdown of the industry distribution for connected WeChat firms and for public firms connected to social media outlets. Notably, 67% of financial firms are connected to social media outlets, which is consistent with expectations given the 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 show how widespread social media connections are across industries.

Panel A of Table 2 reports characteristics of WeChat accounts in our sample. For connected and unconnected accounts at the account-year level, we report (i) account age, (ii) annual posting frequency, and (iii) the breadth of firm coverage (i.e., the number of distinct firms covered). Connected accounts are only slightly older than unconnected accounts, but publish substantially more articles per year and cover a much broader set of firms. These comparisons indicate that our measure of social media connection captures firms' links to active and influential media outlets, rather than to marginal or obscure platforms.

[Insert Table 2 about here]

B. WeChat Article Sentiment

Most of our regression analyses are at the article-firm level, 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 weight the sentiment score by the relatedness score to reflect the extent to which readers receive information about the focal firm from the article.

C. 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. To improve the interpretative precision of our DiD analyses specified in Section IV.A, we focus on the [−10, +10] event window and require each event to include at least one connected WeChat article and one unconnected WeChat 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 286 firm-date events from 54 public firms over 2016–2023, covering 2,031 traditional news articles on event dates and 25,580 WeChat article-firm observations within the [−10, +10] window.

Internet Appendix Table A4 compares the characteristics of the 54 firms in the event-study sample with those of other public firms. The sample firms are slightly larger and older, and exhibit higher leverage and book-to-market ratios, along with lower volatility and turnover, and a greater likelihood of institutional and state ownership. Panel B of Table 2 further reports the summary statistics for articles published around the event window. On the event date, the average firm receives 7.1 articles from traditional news outlets, with a tone score of −0.137, indicating generally negative sentiment. During the [−10, +10] window, the average firm receives 89.4 WeChat articles, including 13.8 from connected accounts (6.4 pre-event and 7.4 post-event) and 75.6 from unconnected accounts (34.0 pre-event and 41.6 post-event). The average tone of WeChat articles over this window is 0.055, likely reflecting the lack of consistently negative coverage in the pre-event window.[7] Internet Appendix Figure A3 revisits the case of *Taihe Group* and illustrates articles published around its negative traditional news coverage on August 14, 2020.

To address concerns that the baseline definition is overly restrictive and limits sample size, we construct two additional, less restrictive samples of negative events. The first retains the bottom-decile cutoff but relaxes the requirement that both connected and unconnected articles be observed in both pre- and post-event windows, requiring such coverage only post-event. This relaxation expands the sample to 639 events covering 148 unique firms. The second further broadens the event definition from the bottom decile to the bottom quartile of daily traditional media tone while maintaining the post-only coverage requirement, yielding 1,401 events covering 222 firms.

D. 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); operating, production, and sales

[7] The summary statistics for WeChat articles are calculated using the final regression sample after applying the fixed-effect structure specified in Section IV.A, rather than the raw event-window sample.

activities (e.g., inventory, raw materials, advertising expenditures, 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., patents, organizational restructuring, and executive hires); strategy, cooperation, and CSR (e.g., corporate alliances, partnerships, and charitable donations); regulatory, legal, and reputational shocks (e.g., regulatory warnings, lawsuits, and bankruptcy); and industry policies and macro-environment (e.g., industry trends, economic outlooks, and global market shifts). For detailed definitions and content of the news topic categories, please refer to Internet Appendix Table A5.

E. Other Firm Characteristics and Activities

To construct stock market and firm-level variables, we obtain raw data 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. The variables we consider include 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.

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.

III. Connection Formation and Connected Social Media Tone

Before turning to our main analysis of how firms leverage these connections to counteract negative traditional media coverage, we first investigate the determinants of connection formation and then assess whether connected social media outlets differ systematically in tone.

In Table 3, we estimate logit models of connection formation, relating an indicator for whether a firm establishes a social media connection over the sample period to firm characteristics measured either in the fixed pre-sample year (2015) or in the year the firm enters the sample. 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, suggesting that firms with greater market presence and stronger valuations are more inclined to engage with social media outlets.

Because our later analysis focuses on whether connected firms use social media to counteract negative traditional media coverage, we also examine whether negative traditional media coverage affects connection formation. In Internet Appendix Table A6, we include traditional media sentiment toward the firm as an additional determinant. The insignificant coefficient suggests that connections are not primarily formed as short-term responses to adverse media shocks, but rather reflect more persistent firm strategies.

[Insert Table 3 about here]

We next examine whether connected social media outlets are systematically more favorable toward affiliated firms. We begin by testing whether connection formation is associated with a change in coverage tone. In Internet Appendix Table A7, we focus on firms that establish a connection during the sample period and compare the tone of articles published by the connected account before and after the connection is formed. The coefficient on *Post connection formation* is positive and statistically significant, indicating that tone becomes more favorable following connection formation.

We then examine whether this pattern holds relative to unconnected outlets covering the same firm. To ensure that connected and unconnected articles are compared against the same information environment, we construct a matched sample centered on each connected article. Specifically, for each article published by a connected WeChat account, we match articles from unconnected accounts covering the same firm within a [−10, +10] window. The resulting article-firm level sample contains 154,286 observations, of which 10.1% are connected articles (see panel C of Table 2 for summary statistics).

Using this matched sample, we estimate regressions of *WeChat tone*, defined as the sentiment of the article toward the focal firm, on *Connect*, an indicator equal to one if the focal firm and the publishing WeChat account have a pre-existing connection measured in the year prior to the article publication date. We include year-month fixed effects and firm-WeChat account pair fixed effects. The latter absorb all time-invariant heterogeneity at the firm-outlet level, so the coefficient is identified from within-pair changes in connection status and is less likely to reflect systematic differences across firms or outlets. The results, reported in Table 4, show that the coefficient on *Connect* lies between 0.019 and 0.023, depending on whether we include baseline controls, and is statistically significant at the 1% level. This represents approximately 30.2–36.5% of the sample mean of *WeChat tone* (0.063), indicating an economically meaningful tone advantage of connected articles over unconnected ones covering the same firm.

[Insert Table 4 about here]

One concern is that the tone advantage of connected outlets may be confounded by firms' own disclosure activities around the same period. To address this, Internet Appendix Table A8 augments the baseline specification in Table 4 by controlling for firms' disclosures through alternative information channels, including clarification announcements, other corporate announcements, the firm's own WeChat official account activities, online investor interactions, and roadshow or earnings briefing events.[8] Specifically, for each WeChat article, we include indicators for whether the firm engages in these channels within the [−5, 0] or [−5, +5] window around the article publication date. The coefficient on *Connect* remains positive, statistically significant, and quantitatively similar in magnitude, indicating that the role of connected outlets is not subsumed by firms' direct disclosure responses.

Finally, while Table 4 compares connected with unconnected WeChat articles, we further compare connected WeChat articles with traditional news articles to characterize how connected outlets fit into the broader information environment. Following the same matching strategy as in Table 4, we match each connected WeChat article with traditional news articles covering the same firm within a [−10, +10] window and estimate an analogous regression. The results, reported in Internet Appendix Table A9, show no statistically significant difference in tone between connected WeChat articles and traditional news articles in the unconditional sample.

IV. Whether Firms Counteract Negative Traditional News Coverage Using Social Media

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

[8] Data on clarification announcements are obtained from the *Listed Firm Announcement Statistics Database* by *CNRDS*, while other corporate announcements are drawn from the *Chinese Listed Firm's Clarification Announcement Database* by *CSMAR*. Data on firms' own WeChat official account publications are obtained from *Datayes*. Information on online investor interactions, roadshows, and earnings briefings is obtained from the *Investor Relations Management Database* by *CNRDS*.

A. Event Study: Connected Outlets' Response to Negative Traditional News Coverage

We use a DiD design to examine whether firms leverage their social media connections to counteract negative traditional news coverage. The event sample construction is detailed in Section II.C. We start our analysis with the most restrictive sample of 286 events and estimate the article-firm level DiD specification:

$$\text{(1)}\quad \textit{WeChat tone}_{i,j,t} = \alpha + \beta \textit{Connect}_{i,j} \times \textit{Post}_t + \gamma \textit{Connect}_{i,j} + \textit{year-month FE} + \textit{event FE} + \textit{event-date FE} + \textit{WeChat firm FE} + \varepsilon_{i,j,t}$$

where the dependent variable is the tone of WeChat article *i* toward firm *j*, with a higher score indicating a more positive tone. 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. Although the formation of firm–social media connections is inherently endogenous, our identification strategy helps alleviate this concern. By conducting article-level analyses within short event windows, we minimize the influence of potential selection bias associated with connection formation, making it unlikely to materially affect our results.

Our primary focus in this 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 5 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, in the baseline event-study setting, the tone advantage of connected articles emerges after negative traditional media coverage.

[Insert Table 5 about here]

As detailed in Section II.C, the sample in Column 1 is the most restrictive: the strict DiD design requires that connected and unconnected articles appear in both the pre- and post-event windows, which yields 286 events covering 54 unique firms. To assess robustness, we progressively relax this restriction. Column 2 retains the bottom-decile cutoff but requires connected articles only in the post-event window, expanding the sample to 639 events covering 148 firms. Column 3 further broadens the event definition by classifying events as firm-dates whose daily average relatedness-adjusted traditional news tone falls within the bottom quartile (rather than the bottom decile used in Columns 1 and 2), while maintaining the post-only article requirement, yielding 1,401 events covering 222 firms (i.e., around 30% of sample firms with social media connections). Across all three samples, the *Connect* × *Post* coefficient remains positive, statistically significant, and quantitatively similar in magnitude, indicating that our results are not driven by the arbitrary choice of sample filters.

As a placebo test, Column 4 of Table 5 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 Column 1. The results show no discernible difference in tone between connected and unconnected articles around positive events. This suggests that the 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]

Based on the sample of 286 negative events, Graph A of Figure 1 depicts the coefficients of a dynamic DiD model, where we interact *Connect* with various relative-to-event-date 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 connected social media outlets respond promptly to negative traditional media coverage by disseminating more favorable narratives. Such responses may help firms reframe adverse events, mitigate reputational damage, and dampen the adverse effects of negative traditional media coverage on stock prices and investor confidence.

Graph B of Figure 1 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.

B. Robustness

To further mitigate concerns related to event sample identification and alternative explanations, we perform a battery of robustness tests. These tests follow equation (1) but apply several model variations, including assigning placebo treatments or event times, altering sample construction methods, adjusting event windows, modifying fixed effects, and controlling for alternative firm disclosure channels.

We first conduct an in-space placebo test by repeating the regression specified in equation (1) 500 times, randomly assigning the *Connect* indicator while maintaining the same proportion of connected articles as in the actual sample. Internet Appendix Figure A4 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 Column 1 of Table 5. This result suggests that the observed treatment effect is less likely driven by random chance or spurious correlations, reinforcing the validity of our findings.

In Panel A of Internet Appendix Table A10, we conduct an in-time placebo test in which the event date is shifted backward, with placebo day zero corresponding to days −5 to −1 in the original 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.

This timing pattern is consistent with connected outlets responding to periods of heightened negative traditional media coverage by publishing more favorable narratives.

In Panel B, we modify the event selection criteria. In Column 1, we identify negative events using all firm-article observations with bottom-decile tone over the full sample period, rather than selecting the bottom-decile sample within each day. The results remain consistent with the baseline finding, with an effect size larger than that reported in Column 1 of Table 5. In Column 2, we adopt a more firm-specific approach: a firm-day is classified as experiencing a negative traditional media coverage event if the daily average tone of traditional news articles covering the firm falls more than one standard deviation below the firm's average tone in the previous year. Unlike the previous approaches that compare news sentiment across firms, this method focuses on deviations from the firm's own historical media tone, offering a more tailored measure of unexpected negative coverage. The DiD coefficient remains positive and statistically significant, further reinforcing the robustness of our findings.

Panel C varies the event window and event-spacing criteria. Columns 1–2 adjust the event window from [−10, +10] in the baseline sample to a narrower [−5, +5] window and a wider [−20, +20] window, respectively. Columns 3–4 impose minimum time intervals of 20 and 30 days between consecutive events, instead of the baseline 15 days. In all specifications, the coefficient on the interaction term remains robust. Internet Appendix Figure A5 presents the corresponding dynamic DiD plots for the analyses in Panels B and C.

Panel D further tests fixed effects adjustments. Using the most restrictive sample of 286 events, 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, further reinforcing the robustness of our findings.

In Panels E and F, we further control for firms' own disclosure activities, as discussed in Section III. Specifically, we include indicators for firms' use of five alternative disclosure channels around the event date: clarification announcements, other firm announcements, the firm's own WeChat official account, online investor interactions, and roadshows or earnings briefings. Panel E defines these indicators over the [−5, 0] window, while Panel F uses the [−5, +5] window. Across both specifications, the coefficient on *Connect* × *Post* remains positive, statistically significant, and similar in magnitude, indicating that the role of connected outlets is not subsumed by firms' direct disclosure activities.

Overall, these robustness tests indicate a consistent pattern: connected social media outlets publish significantly more positive articles immediately after receiving negative coverage in traditional media.

C. Stock Market Reaction to Positive Social Media Narratives

We then 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 2,364 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 6 about here]

Table 6 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 evidence that favorable narratives disseminated through connected media are associated with a partial mitigation of the adverse price impact of negative news.

To disentangle the role of firms' own communication channels from that of connected social media outlets in driving the stock market reaction, we re-estimate the firm-day specification while controlling for other corporate disclosure channels as in Internet Appendix Table A8 and in Panels E and F of Internet Appendix Table A10. The results, reported in Internet Appendix Table A11, show that the coefficient on *Connected day* remains positive and statistically significant, indicating that the market reaction we document is not driven by firms' own disclosure responses.

To further examine whether the positive market reaction reflects a temporary price effect that subsequently reverses, we extend the return window beyond the short horizons reported in Table 6. Specifically, we re-estimate the market-reaction tests using cumulative abnormal returns over the [+3, +5], [+3, +10], [+3, +15], and [+3, +30] windows following connected social media coverage. The results, reported in Internet Appendix Table A12, show that the coefficients on *Connected day* remain positive and do not exhibit a reversal over these longer windows. This evidence suggests that the favorable market reaction associated with connected social media coverage is not quickly undone in the post-event period. While this analysis does not fully resolve whether connected coverage improves or impairs price efficiency, it helps alleviate the concern that the documented positive reaction merely reflects a short-lived mispricing that is subsequently reversed.

D. Additional Analyses

In this subsection, we further examine the scope and boundary conditions of the connected-outlet response documented above. While the baseline results show that connected outlets become more favorable following negative traditional media coverage, it remains unclear whether this pattern varies with firm and outlet characteristics, the nature of the triggering information, or the timing of information arrival. We therefore explore three complementary dimensions: ownership structure, information environment, and event timing.

First, we examine whether the response varies with the ownership status of the focal firm and the WeChat outlet. The direction of this heterogeneity is ex ante ambiguous. On the one hand, SOEs may face weaker market discipline due to implicit government backing, which could reduce their incentives to actively manage media narratives through commercial channels. On the other hand, SOEs are often subject to greater political and reputational scrutiny, which could increase their incentives to manage public narratives following negative coverage. The same dual logic applies to outlet ownership: state-owned WeChat outlets may be less commercially driven, but they may also be more responsive to politically sensitive reputational concerns.

Columns 1–2 of Internet Appendix Table A13 split the sample by focal firm ownership. The *Connect* × *Post* coefficient is positive and statistically significant only in the non-SOE subsample, while it is statistically insignificant for SOEs. Columns 3–4 further split the sample by WeChat outlet ownership and yield a similar pattern: the effect is concentrated among non-state-owned outlets and absent among state-owned outlets. Together, these results suggest that the connected-outlet response is more pronounced in settings where market-oriented incentives are stronger.

Second, we examine whether the response differs across types of media coverage. In particular, we distinguish between coverage that introduces substantively new information ("breaking news") and coverage that reflects follow-up reporting on already-public events. To operationalize this distinction, we measure the textual similarity of traditional news titles on the event date relative to titles published in the [−5, −1] or [−10, −1] pre-event window. Specifically, we represent each title using TF-IDF weighted character-level n-grams (of length 2 and 3) and compute the maximum cosine similarity between event-date and pre-event titles.[9] Lower similarity indicates greater textual novelty.

We classify events as "breaking" if the similarity score falls below 0.4 and as "follow-up" otherwise. The threshold balances two considerations: it must be loose enough to capture coverage with substantively new information ("breaking" news), but not so strict as to be misled by the textual overlap inherent in financial news titles (such as corporate names and standard reporting language). The cutoff also yields a reasonable split of the sample.

Internet Appendix Table A14 re-estimates the event-study regression separately for the two subsamples. Columns 1–2 use the [−5, −1] window to construct the similarity benchmark, while Columns 3–4 use the [−10, −1] window. The results show that the *Connect* × *Post* coefficient remains positive and statistically significant in both subsamples, with somewhat larger magnitude for follow-up coverage. This pattern suggests that the connected-outlet response arises both when new information is released and as coverage continues to

[9] The TF-IDF weighting downweighs generic n-grams that appear across many titles, such as the firm's name, industry terms, or routine reporting words like "announce" or "disclose", so that the resulting similarity score captures event-specific content rather than mechanical lexical overlap. The use of character-level n-grams avoids the need for word segmentation in Chinese and is robust to proper nouns, abbreviations, and novel terms that often confound dictionary-based segmentation tools.

circulate. We further verify that the baseline results are robust after excluding events that overlap with earnings disclosure windows (Internet Appendix Table A15).

Finally, we examine whether firms respond only to realized negative coverage or also to anticipated negative information. While the baseline results focus on responses to realized media shocks, firms may also strategically position themselves around scheduled events, such as earnings announcements, which are observable to firms prior to public release. To study this possibility, we examine earnings announcements as a setting in which negative information can be anticipated. Unlike our baseline event-study design, this analysis focuses on the pre-announcement window.[10] Specifically, examining the [−10, −1] pre-announcement window of annual earnings releases, we find that connected articles are significantly more positive than unconnected articles, particularly when firms subsequently report negative earnings surprises (Internet Appendix Table A16). This pattern suggests that firms engage in pre-event positioning, releasing more favorable narratives ahead of predictable adverse news.

Taken together, these results show that the connected-outlet response is not confined to a single setting but varies systematically with ownership structure, the information environment, and event timing. The response is stronger in market-oriented settings, arises both when new information is released and as coverage evolves, and extends to periods preceding anticipated negative events. These patterns highlight the broad scope of connected social media as a channel through which firms manage information flows under different conditions.

[10] Only a small fraction of baseline events overlap with earnings announcements (25 within the [−5, +5] window and 61 within the [−10, +10] window). Excluding these overlapping events leaves the majority of the sample intact, and the results remain qualitatively unchanged (Internet Appendix Table A15).

V. 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 Internet Appendix Table A5. We identify the topic of each article using *Qwen*, a state-of-the-art LLM developed by Alibaba Cloud for advanced text analysis.

To motivate our discussion, we reference an example in Internet Appendix Figure A3. *Taihe Group*, a firm linked to a social media outlet, experienced a negative traditional news event on August 14, 2020, due to an earnings miss. Column 1 in Internet 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.

[Insert Table 7 about here]

We formally test this hypothesis in Table 7. 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.

Panel C examines heterogeneity in the effects of connected social media coverage depending on the nature of the underlying event—*hard* versus *soft* information. *Hard events* refer to adverse occurrences directly linked to objective firm fundamentals, such as weak earnings performance, bankruptcy, or legal and regulatory violations. These events are typically factual and concrete, leaving firms little room for reinterpretation. By contrast, *soft events* are less tied to concrete fundamentals and often stem from external circumstances or perception-driven narratives, such as macroeconomic downturns, industry sentiment shifts, or CSR-related controversies. Because such events are more ambiguous and open to interpretation, firms may find it easier to influence public perception through narrative framing on social media. In Columns 1–2, we classify an event as hard information if the most frequently mentioned topic label in traditional media articles on the event date falls under either "*Financial performance*" or "*Regulatory, legal, and reputational shocks*". All other events are categorized as soft information. In Columns 3–4, we adopt a broader definition of hard information by additionally including events labeled as "*Market assessment and ratings*", while the remaining events are treated as soft information.

The results show that connected accounts exhibit significantly more positive sentiment only when traditional news coverage centers on soft information. No significant difference is observed when negative traditional coverage focuses on hard information. This pattern suggests that connected social media outlets counteract negative sentiment when the underlying events are subjective or perception-based, but not when they concern concrete, verifiable fundamentals for which firms have limited narrative flexibility.

VI. 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.

A. Incentives

Prior studies show that negative media coverage can adversely affect stock prices (Tetlock (2007)), posing significant challenges for firms engaged in major 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 8 report the results.

[Insert Table 8 about here]

We find that although the coefficients for both subsamples are statistically significant, their magnitudes differ substantially. For firms with acquisitions announced within the following three months, 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 greater incentives to counteract negative traditional news coverage.

Beyond major corporate transactions, 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 8, we perform subsample analyses to compare the treatment effect 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 are associated with more positive connected articles following negative traditional media coverage, consistent with an attempt to counteract unfavorable narratives.

An extension of the stock price stabilization motivation is the concern over managerial careers, as stock market performance is an important input in evaluating managers (e.g., Coughlan and Schmidt (1985), Murphy (1985), Warner, Watts, and Wruck (1988), Jensen and Murphy (1990), and 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 concerns: 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 8. Overall, these results provide supportive evidence for our hypothesis.

B. Effectiveness

In Section VI.A, 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 equal 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 9 about here]

Panel A of Table 9 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 inclusion of deal characteristics and fixed effects specifications. 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 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, consistent with the possibility that social media connections help create more favorable market conditions from which key personnel may benefit.

In Panel C, 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 finding suggests that CEOs and chairmen may benefit from the more favorable information environment associated with social media connections.

VII. Conclusion

This study examines whether firms use connected social media outlets to counteract unfavorable coverage in traditional media. Using Chinese public firms and WeChat Official Accounts, we show that connected outlets portray firms more favorably than unconnected outlets. Following negative traditional media coverage, connected outlets become especially favorable toward the focal firm, suggesting that firms can use social media connections as an indirect channel for managing corporate narratives.

Our evidence further shows that the corporate narrative response is not simply a general increase in favorable communication. Connected outlets shift attention away from short-term negative assessments of market reactions and financial performance and toward longer-term themes such as corporate strategy, R&D, cooperation, human resources, and CSR activities. This pattern is consistent with an optimism-shifting mechanism, whereby connected outlets redirect attention toward more favorable and forward-looking aspects of the firm rather than directly disputing unfavorable news. The effect is concentrated in events involving soft information, where ambiguity leaves greater room for interpretation, and is stronger when firms have greater incentives to stabilize stock prices or when managers face heightened career concerns.

These findings contribute to our understanding of how firms manage media narratives in modern information environments. Prior research has largely viewed social media either as an independent source of market information or as a direct corporate disclosure channel. Our study highlights a different role: social media outlets can also serve as indirectly connected intermediaries through which firms shape corporate narratives. More broadly, the evidence suggests that the boundary between independent information production and corporate influence may be less clear in social media environments than in traditional media markets. As firms, investors, and regulators increasingly rely on social media as a source of corporate information, understanding these indirect channels of influence becomes important for evaluating the credibility, interpretation, and market consequences of firm-related news. Future research may examine whether similar indirect narrative-management channels operate in other media systems and regulatory environments.

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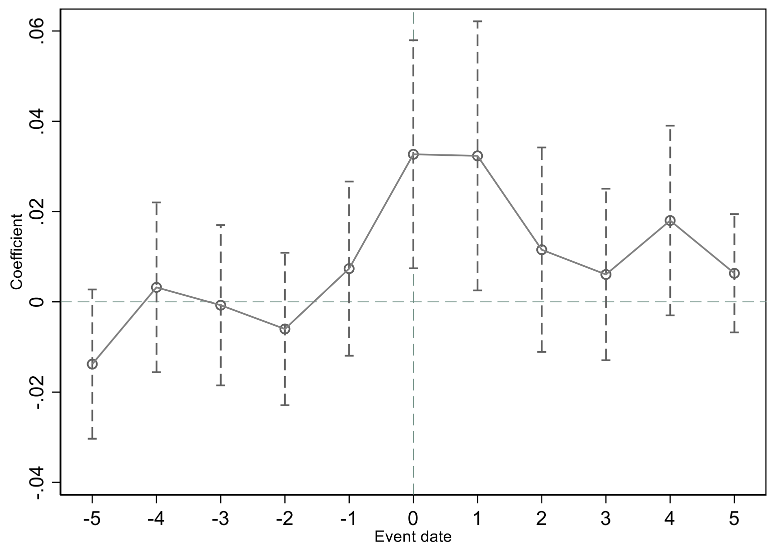
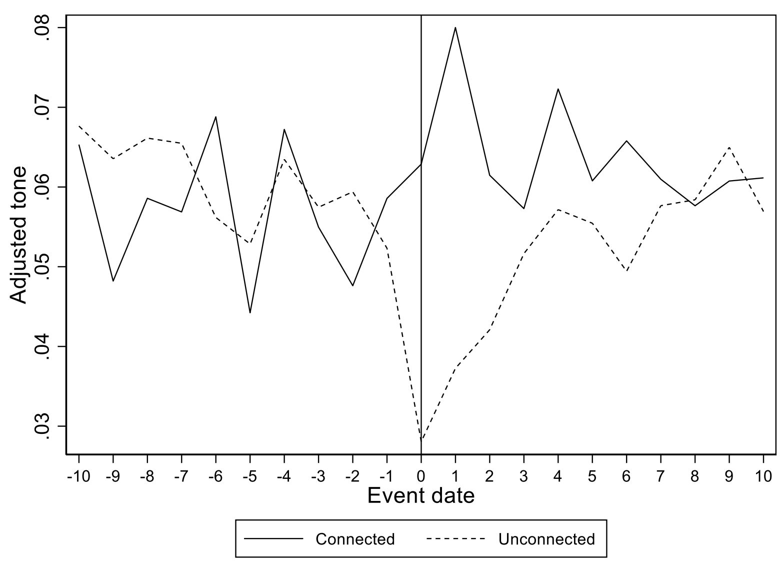
Figure 1. Parallel Trends

This figure presents the results of the parallel trends analyses. Graph A illustrates the estimated coefficients for the interaction between *Connect* and relative event time dummies in the dynamic DiD analysis, with 95% confidence intervals represented by dashed lines. Graph 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).



Graph A. Dynamic DiD



Graph B. Daily Average Tone Score over the Event Window

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 with a relatedness score of one or two. 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 of WeChat Account Characteristics and Main Variables

Panel A compares the characteristics of connected and unconnected WeChat accounts at the account-year level. *Connected accounts* are defined as those that establish a connection with at least one public firm during the sample period, while *unconnected accounts* do not. We examine account age (measured as the difference between the article publication date and the first coverage date), annual posting frequency, and the annual number of firms covered. To ensure comparability, the sample is restricted to corporate-operated accounts. We further restrict the WeChat sample to article–firm pairs with a relatedness score of at least one, in line with the main analyses. Panel B presents summary statistics for variables used in the event study analysis, as well as characteristics of articles published around the event date. The sample consists of 286 events of extremely negative traditional media coverage from 2016 to July 2023, including 2,031 firm-article observations for traditional news published on the event date and 25,580 firm-article observations for WeChat articles published within the [−10, +10] event window. Section II.C describes the event identification procedure in detail. Panel C reports summary statistics for variables used in the article-firm level regression analysis in Section III. All continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Internet Appendix Table A1.

Panel A. Characteristics of Connected vs. Unconnected WeChat Accounts

	Unconnected accounts		Connected accounts		T-test	
	N	Mean	N	Mean	Diff.	*p*-value
Account age	2,815	2.22	826	2.39	-0.17	0.016
Annual posting frequency	2,815	569.03	826	1286.35	-717.32	<0.001
Annual # of firms covered	2,815	191.55	826	391.01	-199.46	<0.001

Panel B. Summary Statistics: Event-Level Analyses

	N	Mean	St. Dev.	Min.	Median	Max.
WeChat tone	25,580	0.055	0.121	-0.299	0.026	0.593
Connect	25,580	0.155	0.362	0.000	0.000	1.000
# of traditional news articles [0]	286	7.101	8.671	1	4	67
Traditional news tone [0]	2,031	-0.137	0.357	-0.991	0.005	0.983
# of WeChat articles [−10, +10]	286	89.441	99.450	4	51	561
# of connected WeChat articles [−10, +10]	286	13.832	24.261	2	4	124
# of connected WeChat articles [−10, −1]	286	6.406	11.666	1	2	67
# of connected WeChat articles [0, +10]	286	7.427	12.900	1	2	59
# of unconnected WeChat articles [−10, +10]	286	75.608	89.055	2	46	469
# of unconnected WeChat articles [−10, −1]	286	34.000	39.528	0	22	286
# of unconnected WeChat articles [0, +10]	286	41.608	54.063	1	25	431

Panel C. Summary Statistics: Article-Firm Level Analyses

	N	Mean	St. Dev.	Min.	Median	Max.
WeChat tone	154,286	0.063	0.121	-0.273	0.029	0.599
Connect	154,286	0.101	0.302	0.000	0.000	1.000
Firm size	154,286	26.639	2.112	21.432	26.980	31.175
Firm age	154,286	2.218	0.928	0.000	2.485	3.434
B/M	154,286	0.782	0.322	0.102	0.941	1.485
ROA	154,286	0.038	0.046	-0.075	0.018	0.203
Leverage	154,286	0.684	0.227	0.126	0.791	0.930
BHAR	154,286	0.132	0.506	-0.465	-0.046	2.139
Volatility	154,286	0.049	0.022	0.016	0.048	0.176
Turnover	154,286	0.879	0.732	0.040	0.707	3.821
Institutional ownership	154,286	0.116	0.090	0.003	0.089	0.637
SOE	154,286	0.474	0.499	0.000	0.000	1.000

Table 3. Formation of Social Media Connection

This table performs logit regressions to examine what types of firms are more likely to have a social media connection. The dependent variable is *Connect*$_{2016–2023}$, an indicator variable that equals one if the firm has ever established a social media connection over our sample period 2016–2023. In Column 1, firm characteristics are measured using data from 2015, and industry fixed effects are included. In Column 2, firm characteristics are measured in the first year the firm enters the sample, and both year and industry fixed effects are included. Internet Appendix Table A1 describes in detail variables employed in the table. Standard errors are heteroskedasticity-robust and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var: *Connect*$_{2016–2023}$	1 Use characteristics in 2015 to predict later connection	2 Use initial year characteristics to predict later connection
Firm size	0.582***	0.520***
	(0.080)	(0.059)
Firm age	0.183**	0.136*
	(0.093)	(0.076)
B/M	-1.215***	-1.148***
	(0.433)	(0.349)
ROA	1.471	0.631
	(1.222)	(0.910)
Leverage	0.309	0.245
	(0.387)	(0.314)
BHAR	0.047	-0.011
	(0.127)	(0.081)
Volatility	4.349*	2.257
	(2.529)	(1.482)
Turnover	0.021	0.000
	(0.042)	(0.032)
Institutional ownership	-0.380	-0.212
	(0.826)	(0.582)
SOE	0.889***	0.792***
	(0.135)	(0.109)
Observations	2,600	4,977
Pseudo R-squared	0.162	0.160
Year FEs	No	Yes
Industry FEs	Yes	Yes
Cluster by firm	No	No

Table 4. Social Media Connection and WeChat Sentiment

This table performs article-firm level OLS regressions to examine the effect of social media connection on the tone of WeChat articles covering the firm. Focusing on article-firm pairs with a medium to high relatedness degree, we first identify WeChat articles published by a connected WeChat Official Account ("connected article") and record the article publishing date. For each connected article, we then match it with articles published 21 days around the publishing date by unconnected WeChat Official Accounts. For comparability, we require both connected and unconnected WeChat articles to be posted by corporate-operated accounts. The sample consists of 154,286 article-firm pairs matched based on 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 one if the firm has established a social media connection in the previous year. We control for year-month and firm-WeChat fixed effects, as well as cluster standard errors at the firm level. Internet Appendix Table A1 describes in detail variables employed in the table. Standard errors are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat tone*	1	2
Connect	**0.023***** **(0.006)**	**0.019***** **(0.006)**
Firm size		-0.014* (0.009)
Firm age		-0.006 (0.009)
B/M		0.006 (0.018)
ROA		0.007 (0.060)
Leverage		0.054 (0.035)
BHAR		0.002 (0.002)
Volatility		0.065 (0.051)
Turnover		-0.006 (0.004)
Institutional ownership		-0.013 (0.033)
SOE		-0.007** (0.003)
Observations	154,286	154,286
R-squared	0.232	0.232
Year-month FEs	Yes	Yes
Firm-WeChat FEs	Yes	Yes
Cluster by firm	Yes	Yes
Mean of the dep. variable	0.063	0.063

Table 5. Whether Firms Counteract Negative Traditional News Coverage Using Social Media

Column 1 of this table performs baseline difference-in-differences 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 one if the firm has established a social media connection in the previous year, and zero otherwise. *Post* is an indicator variable that equals 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 errors at the event level. Section II.C discusses how we identify these negative events in detail. Columns 2 and 3 relax the baseline sample construction by loosening the requirement on article availability across event windows. Specifically, instead of requiring both connected and unconnected articles to be present in both pre- and post-event windows, these columns allow for missing articles in the pre-event window and focus on post-event coverage only. Column 2 retains the bottom-decile event definition, while Column 3 further broadens the sample by using bottom-quartile events. Column 4 presents a placebo test using events with extremely positive traditional media coverage, constructed symmetrically to the baseline sample. Standard errors are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var.	1	2	3	4
= *WeChat tone*		Negative news events		Positive news events
Event identification	Bottom decile (Pre & Post required)	Bottom decile (Post only)	Bottom quartile (Post only)	Top decile (Pre & Post required)
Connect* × *Post	**0.013*** **	**0.016*** **	**0.014*** **	0.008
	(0.005)	**(0.005)**	**(0.004)**	(0.007)
Connect	-0.010	-0.006	-0.001	0.018
	(0.009)	(0.007)	(0.004)	(0.015)
Observations	25,580	39,247	101,263	11,594
R-squared	0.225	0.243	0.216	0.244
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
# events	286	639	1,401	234
# unique firms	54	148	222	49

Table 6. 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 II.C. 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. Standard errors 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***** **(0.001)**	**0.005***** **(0.002)**	**0.006***** **(0.002)**	0.002 (0.001)	**0.004**** **(0.001)**	**0.004**** **(0.002)**
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
Event FEs	No	No	No	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	No	No	No
Cluster by event	No	No	No	Yes	Yes	Yes

Table 7. 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 news 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 *Qwen* as most relevant to the focal firm, with detailed definitions of topic types provided in Internet Appendix Table A5. 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 errors at the event level. In Column 3, we further control for year-month, event, and event date (i.e., relative-to-event-date) fixed effects. Panel C replicates the baseline regression reported in Column 1 of Table 5, separating events into soft information and hard information categories. In Columns 1–2, we classify *hard information events* as those whose most frequently mentioned label in traditional media articles on the event date includes either "*Financial performance*" or "*Regulatory, legal, and reputational shocks*", with all other events categorized as *soft information events*. In Columns 3–4, we further broaden the definition of hard information events to include those labeled as "*Market assessment and ratings*" in addition to the two categories above; all remaining events are classified as soft information events. Standard errors are heteroskedasticity-robust in Column 1 of Panel B, clustered at the event level in all other specifications, and reported in parentheses. "*P*-value Diff. in *Connect* × *Post*" reports the *p*-value from a Fisher permutation test based on 1,000 permutations of the equality of the *Connect* × *Post* coefficients between the paired subsamples. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Topic Distribution

	Traditional media 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**
Regulatory, legal, and reputational shocks	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	1,076	10.89	152	8.75
Operating, 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*****	**-0.117*****
	(0.007)	**(0.024)**	**(0.022)**
Observations	20,210	20,210	20,207
R-squared	0.015	0.015	0.220
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. How Firms Counteract Negative Traditional News Coverage Using Social Media (cont.)

Panel C. Event Study in Column 1 of Table 5: Hard vs. Soft Information Events

	1	2	3	4
Dep. Var.=	Baseline classification		Expanded classification	
WeChat tone	Hard information events	Soft information events	Hard information events	Soft information events
Connect* × *Post	0.011	**0.015****	0.008	**0.025*****
	(0.008)	**(0.007)**	(0.007)	**(0.008)**
Connect	-0.042**	-0.005	-0.012	-0.022
	(0.018)	(0.011)	(0.012)	(0.015)
P*-value Diff. in *Connect* × *Post	0.334		**0.026**	
Observations	7,280	16,706	15,416	8,551
R-squared	0.277	0.241	0.231	0.283
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

Table 8. 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 prices (Panel A) or have greater career concerns (Panel B). The regressions follow the model specified in equation (1). To assess stock price stabilization incentives, we consider whether the firm is going to announce an acquisition within the next three months and whether 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. Standard errors are clustered at the event level and reported in parentheses. "*P*-value Diff. in *Connect* × *Post*" reports the *p*-value from a Fisher permutation test based on 1,000 permutations of the equality of the *Connect* × *Post* coefficients between the paired subsamples. ∗, ∗∗, 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	**0.013**		**0.041**		**0.003**	
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 8. 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***	**0.019***	0.008	**0.018***	0.006
	(0.016)	**(0.006)**	**(0.011)**	(0.006)	**(0.010)**	(0.007)
Connect	-0.041	-0.015	-0.010	-0.013	-0.007	-0.002
	(0.027)	(0.010)	(0.016)	(0.011)	(0.021)	(0.011)
P*-value Diff. in *Connect* × *Post	**0.001**		0.106		0.072	
Observations	2,528	21,564	7,128	16,932	6,890	15,695
R-squared	0.432	0.219	0.281	0.247	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 9. 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 CAPM-based cumulative abnormal returns over the [−1, +1] merger window. In Column 1, we control for baseline firm characteristics, as well as year and firm fixed effects. In Column 2, we further include deal characteristics, including indicators for stock acquisitions, related-party transactions, intellectual property transactions, and major restructuring transactions. Column 3 replaces year fixed effects with year–month fixed effects based on the specification in Column 2. 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. All specifications in Panels B and C include year and firm fixed effects, with standard errors clustered at the firm level. Internet Appendix Table A1 describes in detail variables employed in the table. Standard errors are clustered at the firm level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Acquisition Market Reaction

	1	2	3
	CAR [−1, +1]	*CAR [−1, +1]*	*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 9. Effectiveness of Social Media Connections (cont.)

Panel B. Insider Trading

Dep. Var. =	1	2	3	4
Ln (1+*Insider profits*)	six-month	12-month	six-month (Avg. price)	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 9. 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	**-0.045***	**-0.053****
	(0.023)	**(0.025)**
Firm size	0.003	0.022*
	(0.011)	(0.012)
Firm age	0.103***	0.146***
	(0.015)	(0.016)
B/M	0.063**	0.069**
	(0.029)	(0.031)
ROA	-0.244***	-0.227***
	(0.051)	(0.049)
Leverage	0.009	-0.033
	(0.038)	(0.040)
BHAR	-0.002	-0.002
	(0.006)	(0.006)
Volatility	0.319**	0.285**
	(0.139)	(0.140)
Turnover	0.006**	0.006**
	(0.003)	(0.003)
Institutional ownership	-0.106**	-0.094
	(0.053)	(0.058)
SOE	0.069***	0.059**
	(0.025)	(0.027)
Observations	29,249	29,249
R-squared	0.363	0.488
Year FEs	Yes	Yes
Firm FEs	Yes	Yes
Cluster by firm	Yes	Yes

Internet Appendix

Connected Social Media

Figure A1. Examples of WeChat Official Account

Graph 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

我要联系

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

文 | 李小霞

编辑 | 乔芊 杨轩

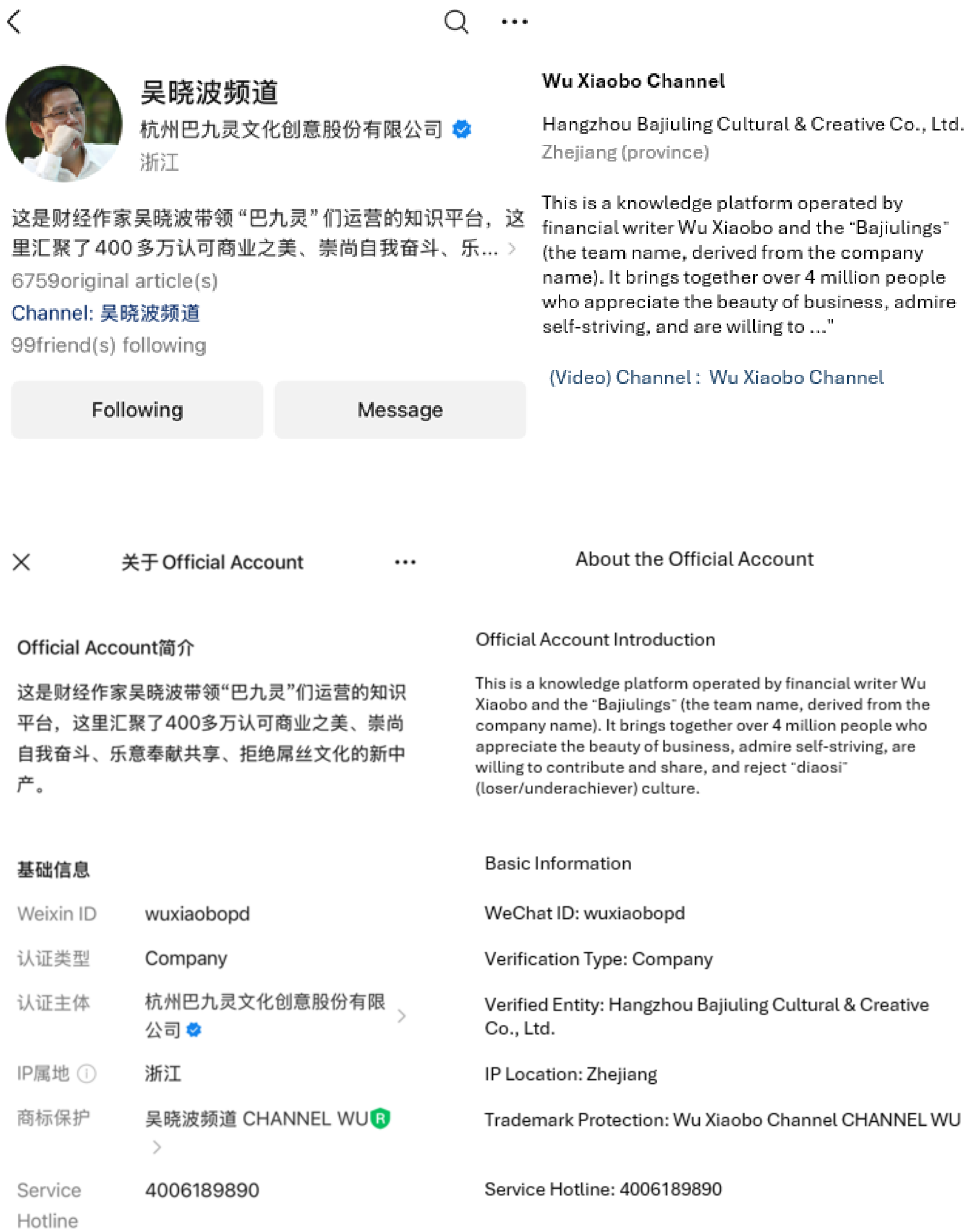
拼多多一直狂奔的海外业务开始明显慢了下来。

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.)

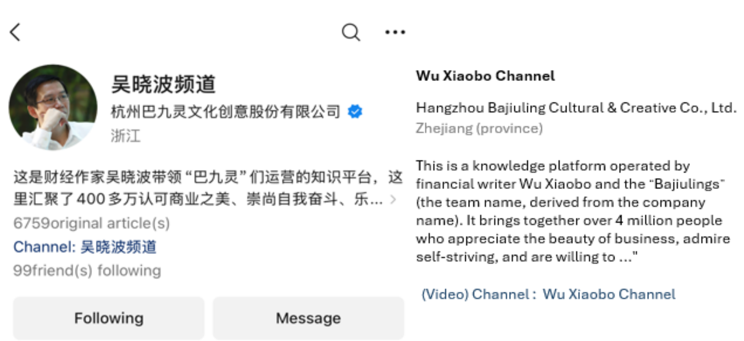
Graph B. Wu Xiaobo Channel



This figure presents 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

Graph A. Wu Xiaobo Channel and Wufangzhai



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 the director concurrently served on both boards.

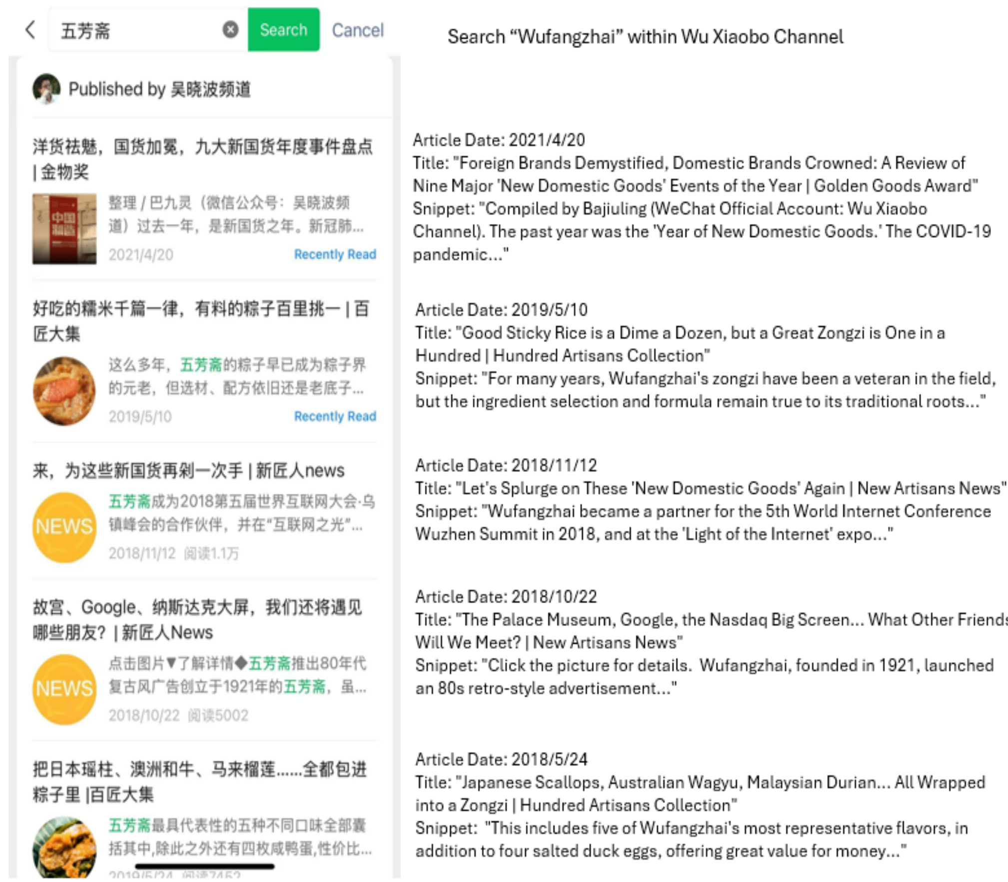


Figure A2. Examples of WeChat Account–Public Firm Connection (cont.)

Graph 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

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..."

The screenshots illustrate that Taihe Group (Tahoe Group Co., Ltd., stock ID 000732.SZ, 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 the WeChat account CRIC Real Estate Research, from 2007 to 2018. Following our definition, the two entities are considered connected beginning in 2007.

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) which faced negative coverage from traditional news outlets on August 14, 2020.

Graph 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 Event Example (cont.)

Graph 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|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. Event Study: 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 equation (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.

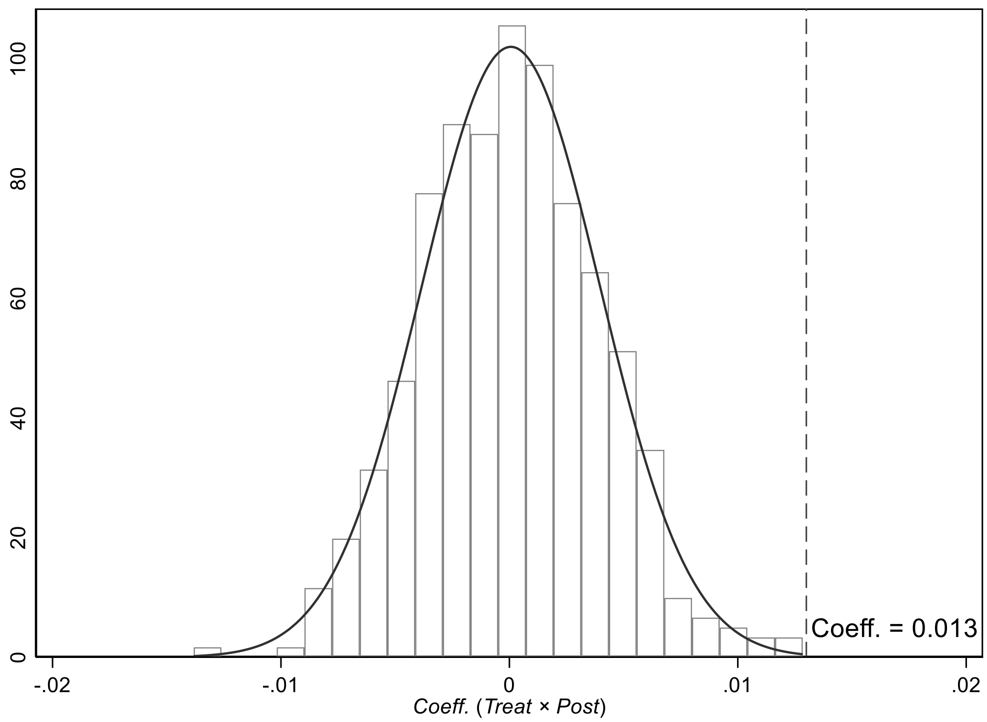
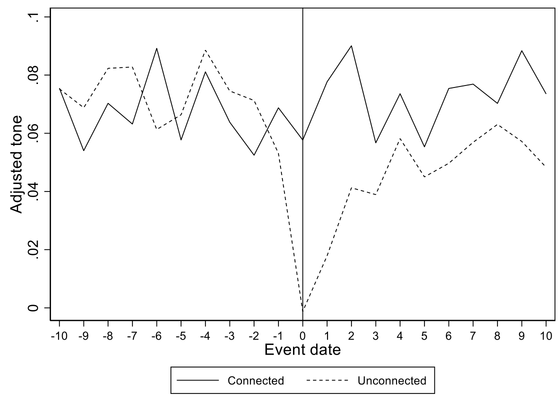
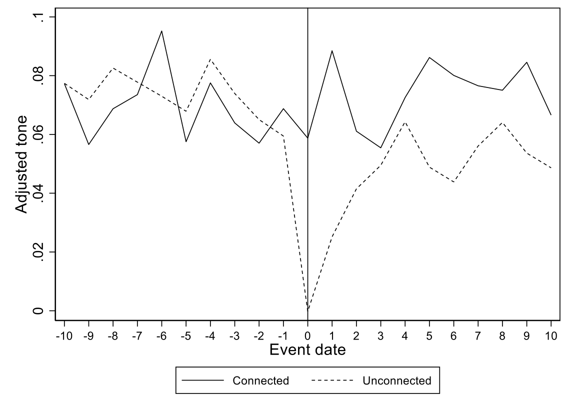


Figure A5. Parallel Trends of Event Study: Robustness Checks

This figure presents the daily average of relatedness-adjusted tone scores for connected and unconnected WeChat articles. Each panel in the figure corresponds to a specific analysis in Table A10. The correspondence between each figure and the analyses in Table A10 is indicated by the figure titles.

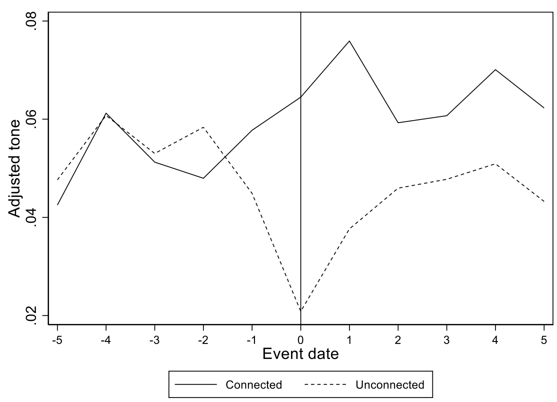


Bottom 10% in all sample

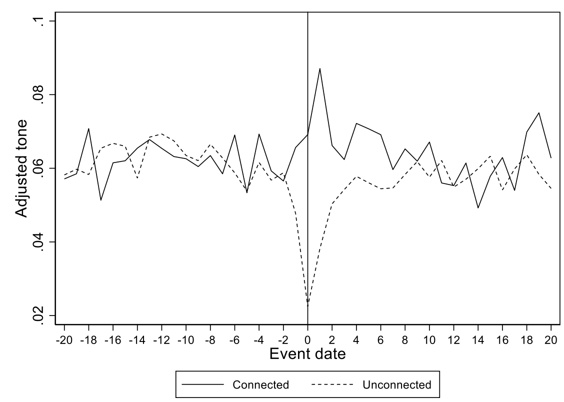


Previous year mean & std

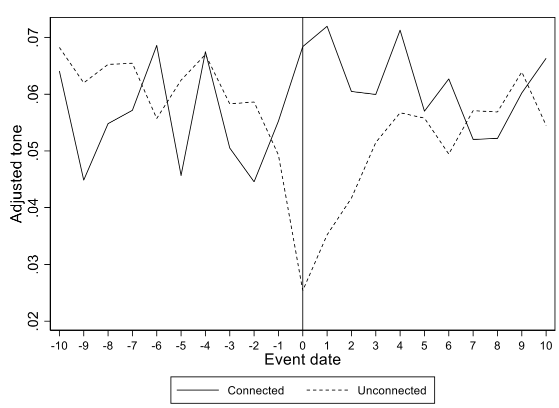
Graph A. Alternative Event Identification Strategies



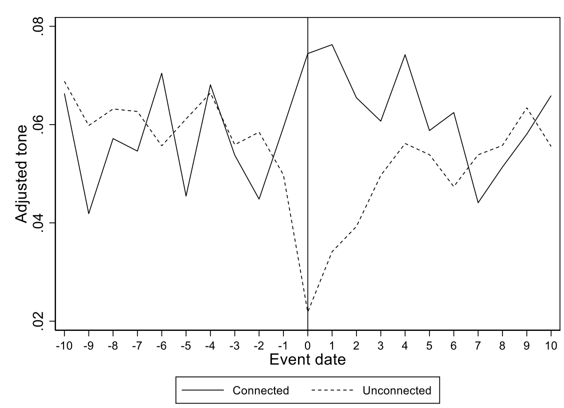
[−5, +5]



[−20, +20]



20 days



30 days

Graph B. Alternative Event Windows or Alternative Minimum Lag Days Between Events

Table A1. Variable Descriptions

Panel A. Social Media Connection	
Connect	An indicator equal to one if the firm has established a social media connection in the year, and zero otherwise. We assume that once established, the connection maintains its status till the end of the sample period.
Connect$_{2016–2023}$	An indicator equal to one if the firm has ever established a social media connection over our sample period 2016–2023, and zero otherwise.
Connected day	An indicator equal to one if at least one article from a connected WeChat account is published for the firm on that day, and zero otherwise.
Panel B. Media Sentiment	
WeChat tone	An article-firm-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.
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 value-weighted market portfolio of all A-share stocks excluding those listed on the ChiNext or STAR markets.
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 equal to one if the firm is ultimately controlled by the government or a government-affiliated entity, and zero otherwise.

Table A1. Variable Descriptions (cont.)

<u>*Panel E. Other Variables*</u>	
Same label	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.
Hard/soft event	Indicators classifying negative traditional media events as hard or soft information events. We adopt two definitions of hard events. Under the narrower definition, hard events are those whose most frequently mentioned topic label in traditional media articles on the event date is "*Financial performance*" or "*Regulatory, legal, and reputational shocks*". Under the broader definition, hard events additionally include events labeled as "*Market assessment and ratings*". Events not classified as hard under each definition are classified as soft information events.
Acquisition within the next three months	An indicator equal to 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 equal to one if the percentage of shares held by the largest shareholder is in the top tercile 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 equal to one if the percentage of shares held by the top management team is in the top tercile in the year, or if the top management team is granted stock options, and zero otherwise.
Poor operating performance	An indicator equal to 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 equal to one if stock return volatility of the firm in the year is in the top tercile within the industry, and zero otherwise.
Short CEO tenure	An indicator equal to 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 et al. (2013).
CEO/Chairman turnover	An indicator equal to 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.

Table A1. Variable Descriptions (cont.)

<u>*Panel F. Variables Employed in the Internet Appendix*</u>	
Traditional media tone	The average sentiment of traditional media coverage received by a firm in a given year. Following the main analysis, we retain article–firm pairs with a relatedness score of at least one. Sentiment for each article–firm pair is measured on a scale from −1, most negative, to 1, most positive, and is weighted by the relatedness score to capture the extent to which the article focuses on the firm. Firm-year traditional media tone is computed as the average of these relatedness-weighted sentiment scores.
Post connection formation	An indicator equal to one if the connection between the firm and the WeChat account has been established in the current year or in any prior year, and zero otherwise.
Clarification	An indicator equal to one if the firm issues a clarification announcement within the specified event window around the article publication date, and zero otherwise.
Announcement	An indicator equal to one if the firm issues an official corporate announcement within the specified event window around the article publication date, and zero otherwise.
Firm WeChat official accounts	An indicator equal to one if the firm publishes at least one article through its own WeChat official account within the specified event window around the article publication date, and zero otherwise.
Online investor interaction	An indicator equal to one if the firm responds to investor inquiries on the stock exchange investor interaction platform within the specified event window around the article publication date, and zero otherwise.
Roadshow & earnings briefing	An indicator equal to one if the firm holds a roadshow, earnings briefing, performance briefing, or similar investor communication event within the specified event window around the article publication date, and zero otherwise.
Focal firm/WeChat firm SOE	An indicator equal to one if the focal public firm (WeChat firm) is ultimately controlled by the government or a government-affiliated entity, and zero otherwise.
Breaking/Follow-up event	Indicators capturing whether a negative traditional media event represents breaking news or follow-up coverage. We classify events based on the similarity between traditional news titles published on the event date and those published during the pre-event window. Specifically, for each event, we compute the maximum title similarity between event-date news and prior news. An event is classified as breaking if the maximum similarity is below 0.4, and as follow-up otherwise.
Negative earnings surprise	An indicator equal to one for firm-years with a negative earnings surprise, and zero otherwise. Earnings surprise is measured as actual EPS minus the consensus analyst forecast EPS, scaled by the stock price two trading days before the annual report disclosure date.

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 accounts other than firms' own 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. Comparing Firm Characteristics of Event Study Sample Firms versus Those of Other Firms
This table presents the results of univariate analyses comparing firm characteristics between the 54 sample firms included in the event study analysis and other publicly listed firms with at least one WeChat article, based on data from the 2022 fiscal year.

	Other firms		Connected firms		T-test	
	N	Mean	N	Mean	Diff.	p-value
Firm size	4,820	22.385	54	24.658	-2.273	**<0.001**
Firm age	4,820	2.048	54	2.552	-0.504	**<0.001**
B/M	4,820	0.666	54	0.759	-0.093	**0.007**
ROA	4,820	0.025	54	0.018	0.007	0.511
Leverage	4,820	0.420	54	0.592	-0.171	**<0.001**
BHAR	4,820	0.026	54	-0.053	0.079	**0.090**
Volatility	4,820	0.065	54	0.054	0.011	**<0.001**
Turnover	4,820	3.255	54	1.877	1.378	**0.001**
Institutional ownership	4,820	0.065	54	0.095	-0.029	**0.027**
SOE	4,820	0.271	54	0.426	-0.155	**0.011**

Table A5. 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 regulatory, legal, and reputational shocks).
Investment/financing activities	Asset transactions, restructuring, acquisitions, IPOs, capital raising activities, and changes in financing costs for activities completed, ongoing, or officially announced.
Operating, production, and sales activities	Core business scope and operations, including expansions, contractions, or modifications to the firm's primary business activities, as well as inventory, raw materials, procurement, production costs, sales, distribution, advertising, and supply chain operations.
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.
Regulatory, legal, and reputational shocks	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.

Table A6. Formation of Social Media Connection: Further Controlling for Traditional Media Sentiment
This table replicates the analyses reported in Table 3, with the additional control for traditional media sentiment. We define *Traditional media tone* as the average sentiment of traditional media coverage received by a firm in a given year. Following the main analysis, we retain article–firm pairs with a relatedness score of at least one. Sentiment for each pair is measured on a scale from −1 (most negative) to 1 (most positive), and is weighted by the relatedness score to reflect the extent to which the article focuses on the firm. Firm-year *Traditional media tone* is then computed as the average of these weighted sentiment scores. As the *Datayes* traditional media dataset is only available from 2016 onward (consistent with the WeChat data), we proxy the 2015 value of *Traditional media tone* using data from 2016. Standard errors are heteroskedasticity-robust and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

	1	2
Dep. Var: *Connect*$_{2016–2023}$	Use characteristics in 2015 to predict later connection	Use initial year characteristics to predict later connection
Traditional media tone	0.721	1.003
	(0.901)	(0.678)
Firm size	0.575***	0.510***
	(0.080)	(0.059)
Firm age	0.194**	0.147*
	(0.093)	(0.076)
B/M	-1.183***	-1.104***
	(0.434)	(0.349)
ROA	1.256	0.396
	(1.249)	(0.923)
Leverage	0.346	0.263
	(0.390)	(0.317)
BHAR	0.060	-0.010
	(0.127)	(0.081)
Volatility	4.442*	2.326
	(2.540)	(1.486)
Turnover	0.009	-0.006
	(0.042)	(0.032)
Institutional ownership	-0.509	-0.309
	(0.847)	(0.583)
SOE	0.896***	0.793***
	(0.136)	(0.109)
Observations	2,596	4,973
Pseudo R-squared	0.163	0.160
Year FEs	No	Yes
Industry FEs	Yes	Yes
Cluster by firm	No	No

Table A7. WeChat Sentiment Before versus After Connection Establishment

This table examines how WeChat sentiment changes following the establishment of a social media connection. The sample is restricted to WeChat–firm pairs that eventually form a connection during the sample period. The dependent variable is *WeChat tone*, where higher values indicate more positive sentiment. *Post connection formation* is an indicator equal to one if the connection between the firm and the WeChat account has been established in the current or previous year, and zero otherwise. Column 1 defines connection status using information from year *t–1*, while Column 2 measures connection status contemporaneously in year *t*. All regressions control for firm characteristics, as well as year-month and firm–WeChat pair fixed effects. Standard errors are clustered at the firm level. Internet Appendix Table A1 describes in detail variables employed in the table. Standard errors are reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat tone*	1 Connection measured at year *t-1*	2 Connection measured at *t*
Post connection formation	**0.029****	**0.041*****
	(0.012)	**(0.014)**
Firm size	-0.031*	-0.029
	(0.018)	(0.019)
Firm age	-0.016	-0.009
	(0.016)	(0.016)
B/M	0.084	0.091*
	(0.053)	(0.052)
ROA	0.136	0.155
	(0.163)	(0.151)
Leverage	0.001	0.013
	(0.063)	(0.062)
BHAR	-0.007	-0.004
	(0.006)	(0.005)
Volatility	-0.318	-0.369
	(0.261)	(0.263)
Turnover	0.010	0.010
	(0.013)	(0.012)
Institutional ownership	-0.006	0.030
	(0.088)	(0.088)
SOE	0.001	-0.005
	(0.015)	(0.014)
Observations	18,406	18,406
R-squared	0.255	0.256
Year-month FEs	Yes	Yes
Firm-WeChat FEs	Yes	Yes
Cluster by firm	Yes	Yes

Table A8. Social Media Connection and WeChat Sentiment: Further Controlling for Other Disclosure Channels

This table replicates the baseline analysis in Table 4 while controlling for firms' information disclosure through alternative channels around the event window. The channels considered include: clarification announcements, other corporate announcements, firm WeChat official accounts (i.e., whether the firm publishes articles), online investor interactions (i.e., whether the firm responds to investor inquiries), and roadshow or earnings briefing events. Panel A uses the [−5, 0] event window, while Panel B uses the [−5, +5] window. Internet Appendix Table A1 provides detailed variable definitions. Standard errors are clustered at the firm level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. [−5, 0] Event Window

Dep. Var. = *WeChat tone*	1	2	3	4	5	6
Connect	**0.019*** **	**0.018*** **	**0.019*** **	**0.019*** **	**0.019*** **	**0.019*** **
	(0.006)	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**
Clarification	-0.019					-0.020
	(0.018)					(0.018)
Announcement		**0.002***				**0.003***
		(0.001)				**(0.001)**
Firm WeChat official accounts			**0.004*** **			**0.004*** **
			(0.001)			**(0.001)**
Online investor interaction				-0.001		-0.001
				(0.001)		(0.001)
Roadshow & earnings briefing					0.003	0.002
					(0.003)	(0.003)
Observations	154,286	154,286	154,286	154,286	154,286	154,286
R-squared	0.232	0.232	0.232	0.232	0.232	0.233
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-WeChat FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. [−5, +5] Event Window

Dep. Var. = *WeChat tone*	1	2	3	4	5	6
Connect	**0.019*** **	**0.018*** **	**0.020*** **	**0.019*** **	**0.019*** **	**0.020*** **
	(0.006)	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**	**(0.006)**
Clarification	-0.012					-0.012
	(0.014)					(0.014)
Announcement		**0.004*** **				**0.004*** **
		(0.002)				**(0.002)**
Firm WeChat official accounts			**0.006*** **			**0.006*** **
			(0.002)			**(0.002)**
Online investor interaction				-0.001		-0.001
				(0.001)		(0.001)
Roadshow & earnings briefing					0.002	0.002
					(0.003)	(0.003)
Observations	154,286	154,286	154,286	154,286	154,286	154,286
R-squared	0.232	0.232	0.232	0.232	0.232	0.233
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-WeChat FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes

Table A9. Sentiment of Connected WeChat versus Traditional News Articles

This table compares the sentiment of connected WeChat articles with that of traditional news articles using a matched-sample design. Following the matching procedure in Table 4, we first identify connected WeChat articles and record their publication dates. For each connected article, we collect traditional news articles published within a [−10, +10] window around the same firm-event. Using this matched sample, we estimate article-firm level regressions where the dependent variable is *WeChat/Traditional media tone*, with higher values indicating more positive sentiment. The independent variable is *Connect*, an indicator equal to one for connected WeChat articles and zero for traditional news articles. In Column 1, we include year-month fixed effects and firm fixed effects, with standard errors clustered at the firm level. In Column 2, we further control for firm characteristics. Internet Appendix Table A1 provides detailed variable definitions. Standard errors are clustered at the firm level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat/Traditional media tone*	1	2
Connect	-0.011	-0.011
	(0.011)	(0.011)
Firm size		-0.019**
		(0.008)
Firm age		0.002
		(0.012)
B/M		0.002
		(0.018)
ROA		0.040
		(0.055)
Leverage		0.044
		(0.036)
BHAR		0.001
		(0.005)
Volatility		-0.048
		(0.118)
Turnover		-0.000
		(0.005)
Institutional ownership		0.043
		(0.041)
SOE		-0.008*
		(0.005)
Observations	1,566,967	1,566,967
R-squared	0.045	0.045
Year-month FEs	Yes	Yes
Firm FEs	Yes	Yes
Cluster by firm	Yes	Yes

Table A10. Event Study: Robustness

This table presents robustness checks to validate the event study results from Column 1 of Table 5. Panel A conducts in-time placebo tests by shifting the treatment period from one to five periods 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 decile across all days in the sample period (Column 1), or below the previous year's average tone by more than one standard deviation (Column 2). Panel C examines alternative event windows ([−5, +5] and [−20, +20]) and minimum lag days between events (20 or 30 days). Panel D imposes stricter controls using relative-date-to-event fixed effects. Panel E and F further extend the event-study specification by controlling for firms' information disclosure through alternative channels within the [−5, 0] and [−5, +5] windows, respectively. Specifically, we include indicators capturing whether the firm discloses information through channels including: clarification announcements, other firm announcements, firm WeChat official accounts, online investor interactions, and roadshows or earnings briefings. Parallel trend test results for these robustness checks are shown in Internet Appendix Figure A5. Standard errors are clustered at the event level and reported in parentheses, and $*$, $**$, and $***$ denote statistical significance at the 10-, 5-, and 1-percent 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.=	1	2
WeChat tone	Bottom 10% in all sample	Previous year mean & std.
Connect* × *Post	**0.028*****	**0.027*****
	(0.007)	**(0.007)**
Connect	-0.006	-0.004
	(0.015)	(0.015)
Observations	13,032	13,714
R-squared	0.274	0.269
Year-month FEs	Yes	Yes
Event FEs	Yes	Yes
Event date FEs	Yes	Yes
WeChat FEs	Yes	Yes
Cluster by event	Yes	Yes

Table A10. Event Study: Robustness (cont.)

Panel C. Alternative Event Windows or Alternative Minimum Lag Days Between Events

Dep. Var.= *WeChat tone*	1	2	3	4
	[−5, +5]	[−20, +20]	20 days	30 days
Connect* × *Post	**0.024*****	**0.007***	**0.014*****	**0.015****
	(0.007)	**(0.004)**	**(0.005)**	**(0.006)**
Connect	-0.025*	0.002	-0.011	-0.013
	(0.015)	(0.006)	(0.009)	(0.010)
Observations	10,598	67,675	23,483	20,684
R-squared	0.250	0.199	0.230	0.230
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. Stricter Fixed Effects

Dep. Var.= *WeChat tone*	1
Connect* × *Post	**0.014****
	(0.007)
Connect	-0.012
	(0.010)
Observations	24,505
R-squared	0.363
WeChat FEs	Yes
Event by Event-date FEs	Yes
Cluster by event	Yes

Table A10. Event Study: Robustness (cont.)

Panel E. Further Controlling for Other Disclosure Channels: [−5, 0] Window

Dep. Var.= *WeChat tone*	1	2	3	4	5	6
Connect* × *Post	**0.014*****	**0.013****	**0.013*****	**0.013****	**0.013****	**0.014*****
	(0.005)	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**
Connect	-0.011	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Clarification	**-0.085*****					**-0.085*****
	(0.023)					**(0.023)**
Announcement		0.003				0.004
		(0.002)				(0.003)
Firm WeChat official account			0.000			0.001
			(0.005)			(0.005)
Online investor interaction				-0.003		-0.001
				(0.003)		(0.002)
Roadshow & earnings briefing					-0.001	-0.000
					(0.007)	(0.007)
Observations	25,580	25,580	25,580	25,580	25,580	25,580
R-squared	0.228	0.225	0.225	0.225	0.225	0.228
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

Panel F. Further Controlling for Other Disclosure Channels: [−5, +5] Window

Dep. Var.= *WeChat tone*	1	2	3	4	5	6
Connect* × *Post	**0.014*****	**0.013****	**0.013****	**0.013****	**0.013****	**0.014*****
	(0.005)	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**	**(0.005)**
Connect	-0.011	-0.010	-0.010	-0.010	-0.010	-0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Clarification	**-0.083*****					**-0.084*****
	(0.030)					**(0.031)**
Announcement		0.004				0.005
		(0.003)				(0.003)
Firm WeChat official account			0.002			0.005
			(0.005)			(0.005)
Online investor interaction				-0.002		-0.001
				(0.003)		(0.003)
Roadshow & earnings briefing					-0.001	-0.001
					(0.006)	(0.006)
Observations	25,580	25,580	25,580	25,580	25,580	25,580
R-squared	0.228	0.225	0.225	0.225	0.225	0.228
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 A11. Stock Market Reactions to Positive Social Media Narratives: Further Controlling for Other Disclosure Channels

This table repeats the analysis in Column 6 of Table 6, further controlling for alternative firm disclosure channels over the [−5, 0] or [−5, +5] window. Specifically, we separately or jointly include indicators capturing whether the firm discloses information through channels including clarification announcements, other firm announcements, firm WeChat official accounts, online investor interactions, and roadshows or earnings briefings. Standard errors are clustered at the event level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Panel A. Further Controlling for Other Disclosure Channels: [−5, 0] Window

Dep. Var. = *CAR [0, +2]*	1	2	3	4	5	6
Connected day	**0.004****	**0.004****	**0.004****	**0.004****	**0.004****	**0.004****
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Clarification	-0.009					-0.009
	(0.007)					(0.007)
Announcement		-0.001				-0.000
		(0.003)				(0.003)
Firm WeChat official account			0.004			0.004
			(0.007)			(0.007)
Online investor interaction				-0.001		-0.001
				(0.003)		(0.003)
Roadshow & earnings briefing					0.005	0.005
					(0.006)	(0.006)
Observations	2,363	2,363	2,363	2,363	2,363	2,363
R-squared	0.424	0.424	0.425	0.424	0.424	0.425
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Further Controlling for Other Disclosure Channels: [−5, +5] Window

Dep. Var. = *CAR [0, +2]*	1	2	3	4	5	6
Connected day	**0.004****	**0.004****	**0.004****	**0.004****	**0.004****	**0.004****
	(0.002)	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.002)**
Clarification	**-0.053***					**-0.053***
	(0.030)					**(0.030)**
Announcement		0.002				0.002
		(0.004)				(0.004)
Firm WeChat official account			-0.003			-0.001
			(0.006)			(0.006)
Online investor interaction				-0.002		-0.003
				(0.004)		(0.004)
Roadshow & earnings briefing					-0.004	-0.004
					(0.008)	(0.008)
Observations	2,363	2,363	2,363	2,363	2,363	2,363
R-squared	0.429	0.424	0.424	0.424	0.424	0.429
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes	Yes

Table A12. Stock Market Reactions to Positive Social Media Narratives: Reversal Tests

This table examines whether the short-term positive market reaction to connected WeChat coverage following negative news events reverses over longer horizons. The analysis is conducted at the firm-day level using the same post-event sample as Table 6. The dependent variables are cumulative abnormal returns measured after the original short-window market reaction, over the [+3, +5], [+3, +10], [+3, +15], and [+3, +30] windows. 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. Columns 1–4 include no additional disclosure controls. Columns 5–8 further control for indicators capturing whether the firm discloses information through alternative channels over the [−5, 0] window, including clarification announcements, other firm announcements, firm WeChat official accounts, online investor interactions, and roadshows or earnings briefings. All regressions include year-month fixed effects and event fixed effects. Standard errors are clustered at the event level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

	1	2	3	4	5	6	7	8
Dep. Var. =	*CAR*	*CAR*	*CAR*	*CAR*	*CAR*	*CAR*	*CAR*	*CAR*
	[+3, +5]	*[+3, +10]*	*[+3, +15]*	*[+3, +30]*	*[+3, +5]*	*[+3, +10]*	*[+3, +15]*	*[+3, +30]*
Connected day	-0.002	-0.000	0.000	0.001	-0.002	-0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Clarification					0.049*	0.028**	0.026*	0.032**
					(0.028)	(0.013)	(0.014)	(0.013)
Announcement					-0.001	-0.005	0.000	0.001
					(0.003)	(0.003)	(0.003)	(0.004)
Firm WeChat official account					-0.001	0.000	-0.007**	-0.003
					(0.005)	(0.006)	(0.004)	(0.007)
Online investor interaction					-0.001	0.004	0.003	0.003
					(0.003)	(0.003)	(0.003)	(0.004)
Roadshow & earnings briefing					0.005	0.014	-0.005	0.021
					(0.009)	(0.012)	(0.007)	(0.014)
Observations	2,368	2,368	2,368	2,368	2,368	2,368	2,368	2,368
R-squared	0.496	0.797	0.870	0.927	0.500	0.799	0.871	0.927
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A13. State-Owned Status of Focal/WeChat Firm

This table examines heterogeneity in the event-study results by state ownership status of the focal public firm or WeChat firm. Columns 1–2 report results for subsamples defined by the ownership of the focal public firm, while Columns 3–4 are based on the ownership of the WeChat firm. *SOE* is an indicator equal to one if the firm is ultimately controlled by the government or a government-affiliated entity, and zero otherwise. Standard errors are clustered at the event level and reported in parentheses. "*P*-value Diff. in *Connect* × *Post*" reports the *p*-value from a Fisher permutation test based on 1,000 permutations of the equality of the *Connect* × *Post* coefficients between the paired subsamples. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat tone*	1 Focal firm *SOE* =1	2 Focal firm *SOE* =0	3 WeChat firm *SOE* =1	4 WeChat firm *SOE* =0
Connect* × *Post	-0.000	**0.016****	0.007	**0.020*****
	(0.008)	**(0.007)**	(0.009)	**(0.006)**
Connect	-0.016	-0.009	-0.013	0.002
	(0.016)	(0.012)	(0.015)	(0.013)
P*-value Diff. in *Connect* × *Post	**0.020**		**0.045**	
Observations	8,424	15,661	8,205	10,915
R-squared	0.258	0.252	0.230	0.223
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

Table A14. Breaking News versus Follow-Up Events

This table repeats the event study analysis in Column 1 of Table 5, distinguishing between breaking news and follow-up coverage events. We classify events based on the similarity between traditional news titles published on the event date and those in the pre-event window. Specifically, for each event, we compute the maximum title similarity between the event date and prior days; events are classified as *breaking* if this similarity is below 0.4, and as *follow-up* otherwise. Columns 1–2 use the [−5, −1] pre-event window, while Columns 3–4 use the [−10, −1] window. Standard errors are clustered at the event level and reported in parentheses. "*P*-value Diff. in *Connect* × *Post*" reports the *p*-value from a Fisher permutation test based on 1,000 permutations of the equality of the *Connect* × *Post* coefficients between the paired subsamples. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat tone* Pre-event window =	1 Breaking events [−5, −1]	2 Follow-up events [−5, −1]	3 Breaking events [−10, −1]	4 Follow-up events [−10, −1]
Connect* × *Post	**0.013****	**0.014***	**0.012***	**0.017****
	(0.006)	**(0.008)**	**(0.007)**	**(0.008)**
Connect	-0.011	-0.007	-0.014	0.011
	(0.010)	(0.029)	(0.010)	(0.029)
P-value Diff. in *Connect* × *Post*	0.495		0.322	
Observations	20,608	4,695	20,037	5,267
R-squared	0.229	0.291	0.225	0.300
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

Table A15. Excluding Events Overlapping with Earnings Disclosures

This table repeats the event study analysis in Column 1 of Table 5, excluding events occurring within the [−5, +5] or [−10, +10] window surrounding corporate earnings disclosures. Standard errors are clustered at the event level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var.= *WeChat tone*	1	2
Earnings disclosure window	[−5, +5]	[−10, +10]
Connect* × *Post	**0.014****	**0.012***
	(0.005)	**(0.006)**
Connect	-0.008	-0.006
	(0.009)	(0.009)
# of events	261	225
Observations	23,601	19,656
R-squared	0.228	0.231
Year-month FEs	Yes	Yes
Event FEs	Yes	Yes
Event date FEs	Yes	Yes
WeChat FEs	Yes	Yes
Cluster by event	Yes	Yes

Table A16. Social Media Connection and WeChat Sentiment over the Pre-Earnings-Announcement Window

This table performs article-firm level OLS regressions to examine whether connected accounts tend to publish articles with more positive sentiment over the pre-earnings-announcement windows. We focus on all WeChat articles posted by corporate-operated WeChat Official Accounts published over the $[-10, -1]$ annual earnings announcement windows. *Earnings surprise* is measured as actual EPS minus the consensus analyst forecast EPS, scaled by the stock price two trading days prior to the annual report disclosure date. An earnings surprise is classified as negative when this measure is below zero. The dependent variable is *WeChat tone*, where a greater value indicates a more positive WeChat tone. *Connect* is an indicator variable that equals one if the firm has established a social media connection in the previous year. We control for year-month and firm-WeChat fixed effects, as well as cluster standard errors at the firm level. Internet Appendix Table A1 describes in detail variables employed in the table. Standard errors are reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10-, 5-, and 1-percent levels, respectively.

Dep. Var. = *WeChat tone*	1	2
Earnings disclosure sample =	All	Negative earnings surprise
Connect	**0.054*** **	**0.054** **
	(0.020)	**(0.021)**
Firm size	-0.023***	-0.035**
	(0.008)	(0.014)
Firm age	-0.004	-0.006
	(0.011)	(0.020)
B/M	0.008	-0.020
	(0.022)	(0.031)
ROA	0.028	0.040
	(0.050)	(0.073)
Leverage	0.030	0.006
	(0.045)	(0.066)
BHAR	0.007**	0.004
	(0.003)	(0.006)
Volatility	-0.070	-0.248
	(0.130)	(0.199)
Turnover	-0.005*	-0.005
	(0.003)	(0.004)
Institutional ownership	-0.096**	-0.141*
	(0.048)	(0.072)
SOE	0.002	-0.003
	(0.008)	(0.011)
Observations	37,658	24,605
R-squared	0.458	0.482
Year-month FEs	Yes	Yes
Firm-WeChat FEs	Yes	Yes
Cluster by firm	Yes	Yes
Mean of the dep. variable	0.089	0.088