The Costs of Silence: The Impact of Misinformation Regulation on Finfluencers and Corporate Information Environment*

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ABSTRACT

Using the unique context of social media censorship in China, we investigate how misinformation regulation on investor-focused social media platforms influences the behavior of platform influencers (i.e., finfluencers) and its subsequent effects on capital markets. Our findings reveal that misinformation regulation significantly increases account deletions among finfluencers, particularly those exhibiting a more negative tone prior to the regulation. Additionally, remaining finfluencers respond strategically by posting fewer messages and adopting a more positive tone in their content. Despite these behavioral adjustments, the regulation proves ineffective in enhancing the corporate information environment. This is evidenced by a decline in price informativeness, as reflected in weaker correlations between current stock prices and future earnings news, alongside heightened short-term market reactions to earnings announcements. Furthermore, we provide indirect evidence of potential regulatory capture amidst misinformation regulation. Overall, our results underscore the need for caution when implementing regulatory interventions on investor-focused social media platforms.

Keywords: Misinformation; Social Media Censorship; Information in Digital Spaces; Corporate Information Environment

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1. Introduction

Traditional economic theories suggest that governments are neither motivated (Stigler, 1971) nor competent (Hayek, 1945) in market information governance, while the recent advance shows that well-designed regulatory interventions can effectively curtail online misinformation (Acemoglu et al., 2024). Against the backdrop of increasing threats of misinformation, this study examines whether government regulators can effectively curtail misinformation in digital spaces, such as investor-focused social media, leading to improved corporate information environment.

Over the past decade, social media has changed the corporate disclosure and information environment of financial markets (e.g., Chen et al., 2014; Miller and Skinner, 2015). The SEC has highlighted that "social media is landscape-shifting," with its relevance to financial markets only growing (SEC 2012, p. 1). On the one hand, social media provides firms with a direct way of disseminating information to stakeholders, enriching the information channel between market participants. On the other hand, however, social media promotes the democratization of information, which allows external parties to widely share individual views about firms at little cost, thereby weakening firms' ability to control their information environment. At the same time, the absence of effective regulation on social media may foster the widespread dissemination of fake news among market participants (Vosoughi et al., 2018). For example, Jia et al. (2020) show that social media can distort price discovery in the presence of highly speculative rumors, cautioning that social media can be a rumor mill.

In fact, recent anecdotal evidence from Wallstreetbets (WSB) suggests the presence of misinformation on social media and reveals its severe market consequences. The main concern can be summed up with the following quote in congressional hearings of GameStop Event (GME)[1]: "The Reddit discussions are in many ways quite worrisome. They create volatility in the markets, and volatility is generally bad. It creates all kinds of dislocations." Some immediate actions

[1] Game stopped? Who wins and loses when short sellers, social media, and retail investors collide, Part II. House Hearings 117 Congress (2021), (testimony of Alan Grujic). Available at: Link

were taken by Reddit moderators in the US post-GME, such as temporary closure of the subreddit and servers.[2] Notwithstanding, Bradley et al. (2023) indicate that, the informativeness of online reports has deteriorated post-GME because of the changed content on WSB. Furthermore, in addition to the inherent dangers posed by misinformation *per se*, the proliferation of misinformation on social media has also undermined the credibility of truthful information. Kogan et al. (2023) find that the public has even discounted legitimate information sources due to distrust after the revelation of fraud on social media, crowding out legitimate information production. In this context, it is essential to assess the overall desirability, economic efficiency, and aggregate outcomes of government regulation of online misinformation (Leuz and Wysocki, 2008). A key consideration is whether regulators act in the public interest (Levine and Forrence, 1990) or are subject to regulatory capture (Stigler, 1971; Laffont and Tirole, 1991), as this distinction significantly alters stakeholders' behavior and, in turn, impacts the allocative efficiency of capital markets.

In this study, we utilize a unique setting of social media censorship in China, the 2023 Qinglang Operation, to identify the government's censorship of online misinformation. The 2023 Qinglang Operation is a negative-message-focused misinformation regulation. During this period, the central and local Cyberspace Administrations enforce strict censorship of online negative misinformation regarding firms. In the context of this paper, we primarily focus on how the 2023 Qinglang Operation censors the Eastmoney Guba platforms (the largest social media investing platform in China) and examine whether regulators can effectively curtail misinformation in digital spaces and improve corporate information environment. Specifically, we concrete this general question into a testable one from two perspectives: **1)** how negative-message-focused misinformation regulation (hereafter, misinformation regulation) on investor-focused social media (hereafter, social media) affects platform influencers' (i.e., finfluencers') behavior, and **2)** how

[2] The Verge, Available at: Link

misinformation regulation eventually affects market reactions to contemporaneous and future earnings news through its impacts on corporate information environment.

It is important to clarify the definition of misinformation in this paper before any further discussion. Vosoughi et al. (2018) define "misinformation" as any asserted claim of which the veracity has been verified as false. In contrast, the term "disinformation" implies a deliberate intent to deceive and a willful distortion of truth (Xu, 2021; Li et al., 2023). The distinction between misinformation and disinformation relies on the intent of the sender, emphasizing that disinformation involves a clear intent to mislead, while misinformation may not. Although the 2023 Qinglang Operation claims its regulatory focus of "disinformation," the intent of false information is difficult to prove. Therefore, we use the term "misinformation" throughout the whole paper, yet without any claims about the intent of false information purveyors.

We hypothesize that misinformation regulation on social media significantly changes platform finfluencers' behavior. Misinformation regulation is more likely to target finfluencers due to their central role in shaping public discourse and amplifying economic narratives (Jackson, 2008; Shiller, 2017; Shiller, 2020). We argue that the regulation may make a difference through two channels: direct account deletion and impacts on finfluencers' information production. Due to the asymmetries in regulatory scrutiny (Xu, 2021; Li et al., 2023), negative information is more likely to be censored. Consequently, regulators are more likely to delete finfluencers with more negative tones. At the same time, the remaining non-deleted finfluencers might strategically adjust their posting behavior to remain compliant by adopting more positive sentiment and reducing negative content. Nevertheless, the competitive dynamics on social media may also encourage non-deleted finfluencers to substitute for deleted ones, producing more content, even negative, to fill the void left by those deleted (Galperti and Trevino, 2020). The interplay between these opposing forces makes the regulatory consequence uncertain and an empirical question.

The impact of misinformation regulation extends beyond finfluencers' behavior to capital market consequences. Finfluencers play a pivotal role in financial markets by disseminating information and shaping investor perceptions, acting as social media analysts (Call et al., 2023; Drake et al., 2023). When misinformation regulation reshapes finfluencers' posting behavior, it inevitably alters the information flow within financial markets, ultimately affecting the corporate information environment. This shift in the corporate information environment eventually impacts market reactions to earnings announcements (EA). Specifically, changes in the corporate information environment influence the degree to which valid information is incorporated into price discovery before EA (Ball and Brown, 1968; Kim and Verrecchia, 1991; Demski and Feltham, 1994; McNichols and Trueman, 1994). Consequently, these changes result in either more muted or stronger market reactions. To assess the efficacy of misinformation regulation, we analyze Earnings Response Coefficient (ERC) and Future Earnings Response Coefficient (FERC). ERC measures the short-term market reactions to EA, and FERC measures the degree to which current prices reflect future earnings news regarding firms' fundamentals. Effective regulation improves the corporate information environment overall by curbing misinformation, which mitigates over-optimism (over-pessimism) hyped (depressed) by misleading information before EA. Consequently, market reactions to subsequent EA should be more muted, as the efficient information environment would have efficiently revealed earnings information into prices ex-ante. Additionally, a better corporate information environment can also reduce uncertainty, rendering current prices more informative for future earnings news. In summary, effective misinformation regulation should result in lower ERC and higher FERC, while ineffective one causes opposite changes for both.

The empirical evidence indicates that misinformation regulation significantly impacts platform finfluencers' posting behavior and capital market consequences. First, for deleted finfluencers, we find that finfluencers with more negative tones are more likely to be targeted for account deletion post-regulation. Our conclusion still holds after using penalized maximum likelihood estimations to address the rare-event biases. Second, for non-deleted finfluencers, we find that they strategically adjust their posting behavior post-regulation. Compared to non-deleted active regular users, non-deleted finfluencers exhibit a significant shift towards more positive sentiment and a reduction in the volume of all types of their posts. The semi-elasticity estimates show that, compared to non-deleted active regular users, the number of non-deleted finfluencers' negative posts decreases by 1.094%, and their positive posts declines by 7.318% after the regulation. The heterogeneity analysis reveals that ex-ante cautious finfluencers show more pronounced adjustments in their posting behavior in response to the misinformation regulation.

Next, we show that the misinformation regulation has unintended negative consequences on the corporate information environment, resulting in reduced informational efficiency of stock prices. The empirical results reveal that misinformation regulation exacerbated the inefficiency of price discovery before EA post-regulation. Specifically, ERC increases significantly for the firms more significantly affected by the regulation (target firms) post-regulation. This suggests that information is not efficiently impounded into prices before EA, rendering significant market adjustments after EA to correct ex-ante mispricing. Similarly, target firms' FERC declines after the regulation, showing that the realized prices within fiscal quarters are less informative for future earnings fundamentals post-regulation. Moreover, we show that the negative-message-focused nature of the regulation introduces treatment effect heterogeneity. The ERC model indicates that firms experiencing current negative earnings surprise face heightened contemporaneous short-term market reactions to EA post-regulation, while firms with positive earnings surprise do not. Meanwhile, the FERC model reveals that the price informativeness equally deteriorates for firms with all types of earnings surprise post-regulation. These results indicate that misinformation regulation has suppressed negative news to the detriment of market efficiency, suggesting possibilities of regulatory capture amidst regulation. Taken together, these findings are consistent with the argument by Stigler (1971) and Hayek (1945) that governments are neither motivated nor competent in effectively regulating market information, even in the digital spaces.

To attribute the observed capital market effects to the misinformation regulation requires our difference-in-differences design to be causally interpretable. Nevertheless, as Chinese regulators do not explicitly disclose their regulatory targets, our identified treatment is not perfectly exogenous for plausible causal inference. We conduct a series of robustness tests to address the general concern. First, we validate the absence of diverging trends pre-treatment to gauge the plausibility of parallel trends assumption and ensure the internal validity of our inference. Second, the treatment status is assigned based on the ex-ante likelihood of firms being affected by misinformation regulation. Since we can observe the account deletion post-regulation, we use the ex-post treatment outcomes to verify the validity of our ex-ante treatment identification. Third, we conduct re-randomization tests (Fisher et al., 1966; Anderson and Robinson, 2001) to mitigate concern that spurious correlations drive our findings due to endogenous treatment assignment and treated timing. Fourth, although we use Propensity Score Matching (PSM) to mitigate endogeneity issues for treatment identification, it is impossible to fully rule out all possible confounders. To address this concern, we apply the Oster (2019) test and show that the omitted variables are unlikely to drive our results. Last, we also relax the PSM caliper to guarantee the tradeoffs between generalizability and causality and mitigate the concern of "manipulation" inherent in PSM to some extent.

This research contributes to two strands of literature. First, our research feeds into the scanty literature on misinformation on social media (e.g., Clarke et al., 2021; Xu, 2021; Kogan et al., 2023; Crowley et al., 2023; Li et al., 2023). While previous studies focus on the effects of ex-post verified misinformation (e.g., fake news on social media verified by the SEC), our paper examines the effects of ex-ante precautionary regulation of misinformation. Clarke et al. (2021) and Kogan et al. (2023) document the direct impact of ex-post verified fake news on market reactions and its indirect negative spillover effect on legitimate information production. Using ex-post verified fake news data, Xu (2021) and Li et al. (2023) identify the determinants and consequences of firms being targeted by misinformation. Our paper shifts the focus to the ex-ante precautionary misinformation regulation on investor-focused social media. It builds upon the work of Crowley et al. (2023), which investigates the impact of misinformation regulation on corporate social media strategy and corporate transparency across multiple countries. In contrast, we focus on the impact of misinformation regulation on finfluencers' posting behavior and market reactions with regard to contemporaneous and future earnings news. More importantly, this paper validates the key assumption of Crowley et al. (2023): the misinformation regulation significantly changes the corporate online information environment, therefore prompting corporations to adjust their social media strategies accordingly.

Second, we contribute to the literature on government control of information. Traditional economic theories suggest governments are neither motivated (Stigler, 1971) nor competent (Hayek, 1945) in effectively regulating information. Yet the recent advance shows that well-designed regulatory interventions can effectively curtail online misinformation (Acemoglu et al., 2024). Against this backdrop, we offer a unique empirical perspective on government information control in digital spaces. Previous research has extensively examined this issue in the context of traditional media, with most findings suggesting that government control undermines media independence, introduces political bias, and hinders media's role as a disciplinary force (Zhao, 2000; Miller, 2006; Piotroski et al., 2017; Qin et al., 2018; You et al., 2018). Nonetheless, government intervention is still necessary to prevent excessive commercialization within the media industry, which could lead to biases aimed at catering to audiences (Core et al., 2008). In the context of social media, a growing literature in other disciplines highlights that political actors intervene on online platforms for various purposes, such as strategically distracting the public or shifting discussions (Tucker et al., 2017; King and Roberts, 2017). However, little is known about how government control of information on investor-focused social media platforms affects financial markets, which we study in this research. Furthermore, the experience of government control over traditional media cannot be fully generalized to social media, given the significant differences in audience reach and information dissemination patterns. Our study provides a unique perspective regarding government intervention in digital spaces, particularly the relevant economic trade-offs behind measures such as direct censorship.

A caveat is worth noting when interpreting our findings. This study is based on the institutional context of China's media censorship and Chinese financial markets. Therefore, our findings may not be generalizable to global markets. Notwithstanding, we provide a unique perspective on how capital markets operate under stringent censorship in digital spaces.

The remainder of the paper is organized as follows. Section 2 elaborates on the hypothesis development. Section 3 lays out the institutional setting, data collection, and the construction of main variables. Following that, sections 4 and 5 present the empirical specifications and sample summary. Section 6 shows the account deletions under the misinformation regulation. Section 7 analyzes how the misinformation regulation affects non-deleted finfluencers' posting behavior. Section 8 delves into the realized capital market effects of misinformation regulation. Finally, we conclude our findings and implications in section 9.

2. Hypothesis Development

While there are many different users on social media, our focus is on finfluencers, referring to individuals who use social media platforms to share financial insights, investment strategies, personal finance tips, and opinions on market trends. This focus follows an implicit universal assumption that misinformation regulation primarily targets finfluencers due to the associated censorship costs and policy objectives. First, targeting finfluencers directly can reduce the cost of information censorship, as monitoring a broad base of regular users is prohibitively expensive. Second, from a regulatory perspective, finfluencers are more likely to create market volatility, and regulators should closely oversee them. They are influential in affecting and coordinating regular users' behavior by actively creating posts and spreading information, eventually triggering market-wide volatility. As Jackson (2008) highlights the importance of network structures, finfluencers build trust and credibility with their followers through their centrality in networks. This centrality allows finfluencers to make public discourse with significant influence. In this context, their expressions often transcend personal beliefs and become "economic narratives" (Shiller, 2017; 2020), which may go viral and grant finfluencers an outsized impact over regular users and the broader community.

2.1 Hypothesis 1

Regulators enforce misinformation regulation through two primary measures: censorship and account deletion. To begin with, they usually adopt milder censorship approaches, such as filtering potential misinformation out ex-ante or censoring and deleting published misleading posts ex-post. In more serious cases, regulators may directly delete relevant users' accounts (i.e., account suspension or forced deregistration) (Zhang et al., 2023). As a result, an increase in finfluencers' account deletion is expected after the misinformation regulation.

However, regulators cannot precisely differentiate misinformation and disinformation because they cannot accurately judge users' intent. Given the limited user information, regulatory judgments rely primarily on observed posting behavior. Xu (2021) highlights asymmetries in regulatory scrutiny, noting that negative information is more likely to be censored. Li et al. (2023) indicate that negative misinformation is significantly more prevalent than positive ones. Consequently, finfluencers with negative messages are more likely to attract regulatory attention and face account deletion. Therefore, compared to the pre-regulation period, we predict that finfluencers using more negative tones are more likely to be targeted for deletion post-regulation, as outlined below:

H1: Compared to the pre-regulation period, finfluencers with more negative tones are more likely to be targeted for deletion post-regulation.

2.2 Hypothesis 2

Next, we examine the impact of misinformation regulation on non-deleted finfluencers' posting behavior. Specifically, we analyze three outcomes on a monthly basis: the sentiment intensity, the number of negative posts, and the number of positive posts. Sentiment intensity reflects the changes in users' emotional expression, and the number of negative (positive) posts tracks the shifts in the number of pessimistic (optimistic) narratives.

We first discuss the impact of misinformation regulation on non-deleted finfluencers' sentiment and negative posts, as they are more directly affected by the regulation. Previous research shows that government affects media content (e.g., You et al., 2018). Studies such as Xu (2021) and Li et al. (2023), along with the discussion in H1, highlight that regulators primarily target and censor negative messages. Consequently, after the regulation, non-deleted finfluencers might strategically adjust their behavior to remain compliant by adopting more positive sentiment and reducing negative content production, which we term the deterrence hypothesis.

While the deterrence hypothesis focuses on individual finfluencers' strategic compliance, it does not fully account for the broad dynamics within social media, where competition for attention plays a role. Galperti and Trevino (2020) present a theoretical model on the endogenous provision and acquisition of information, highlighting that competition for attention can lead to a homogeneous supply of information. In this context, as some finfluencers are removed post-regulation, the remaining non-deleted finfluencers may quickly take over their portion in social media, supplying content similar to that of the deleted finfluencers to capture their audience, which we call the internal substitution hypothesis. Building on the prediction in H1, given that deleted finfluencers typically produce a large amount of negative content prior to their removal, non-deleted finfluencers may complement the void left behind by offering more homogeneous negative content so as to meet followers' demand. As a result, their sentiment intensity might become more negative, and the number of negative posts may increase accordingly. Since the impact of misinformation regulation on non-deleted finfluencers' posting behavior is unclear ex-ante, we state our hypotheses in the null form:

H2a: The misinformation regulation does not affect the sentiment intensity of non-deleted finfluencers.

H2b: The misinformation regulation does not affect the number of non-deleted finfluencers' negative posts.

We also consider the impact of misinformation regulation on the production of positive content, which remains uncertain ex-ante due to several possibilities. On the one hand, the deterrence hypothesis suggests that non-deleted finfluencers may strategically reduce negative posts while simultaneously increasing positive ones to avoid regulatory scrutiny. On the other hand, non-deleted finfluencers may engage in self-censorship after becoming aware of the regulation, filtering even their positive content to avoid anything they perceive as inappropriate or potentially in violation of the rules. Meanwhile, regulators, constrained by their limited capacity to judge information accurately (Hayek, 1945), may not only target positive misinformation but also mistakenly suppress truthful, positive content. Given these competing dynamics, the net effect on the number of positive posts remains unclear ex-ante. We thus summarize in the null form:

H2c: The misinformation regulation does not affect the number of non-deleted finfluencers' positive posts.

2.3 Hypothesis 3

Lastly, we investigate the capital market effects of regulating misinformation on social media. Finfluencers on social media propel the democratization of finance by acting as social media analysts. Call et al. (2023) highlight their crucial role in enhancing price discovery. In some cases, these finfluencers even outperform professional sell-side analysts (Drake et al., 2023). However, an investigation[3] by Richard Pearson and the SEC provides substantial evidence that KOLs on Seeking Alpha colluded with other parties, such as institutional investors and firms, to release misinformation and mislead investors (Kogan et al., 2023). As misinformation regulation reshapes the finfluencers' posting behavior and thus changes the corporate information environment, we expect this may impose effects on capital markets.

EA discloses the firms' operational status, providing a basis for ex-post identification of misinformation spread prior to the EA. In our study, we define misinformation as wrong information that is contrary to the truth presented in EA (for details, see the confusion matrix of Figure OA-1 in online appendix). Based on the Efficient Market Hypothesis (Fama, 1970), market

[3] Seeking Alpha, available at: Link

reactions to EA reflect to which degree the valid information enters ex-ante price discovery (Ball and Brown, 1968; Kim and Verrecchia, 1991; Demski and Feltham, 1994; McNichols and Trueman, 1994), and we thus evaluate the efficacy of the misinformation regulation through this lens. Specifically, we utilize ERC and FERC to capture market reactions, thereby assessing the corporate information environment. ERC measures the short-term market reactions to EA. FERC measures the degree to which current prices reflect future earnings news with respect to firms' fundamentals. We differentiate market reactions with regard to contemporaneous and future earnings news through ERC and FERC, respectively.

Before the formal analysis, we first define two types of regulation: effective regulation and ineffective regulation. Misinformation regulation may inadvertently suppress valid information, as some finfluencers may produce both legitimate and illegitimate content. Thereby, we assess regulations based on the net effect of regulatory consequences. Effective regulation refers to misinformation regulation with net effects that, on balance, improve the corporate information environment. In contrast, ineffective regulation fails to achieve this objective.

Our analysis begins with the hypothesis of effective regulation (see Figure 1a. Effective regulation). Before misinformation regulation, finfluencers may disseminate negative (positive) misinformation, and this will depress (hype) stock prices before EA. Consequently, there will be significant market adjustment when truthful positive (negative) earnings news is verified in EA, reflected by a higher ERC in the pre-regulation period. After the regulation, the corporate information environment is improved as regulators effectively eliminate misinformation. As a result, short-term market reactions to EA will be muted because the information is efficiently revealed in prices before EA, making ERC lower in the post period. For FERC, prior to the regulation, if finfluencers spread negative (positive) misinformation that contradicts future earnings news, current prices cannot reflect future fundamental information because the misinformation curbs the price discovery, resulting in a lower FERC in the pre-regulation period. After regulation, effective regulation can prevent negative (positive) misinformation and improve the corporate information environment, thereby reducing the uncertainty regarding future earnings news. FERC will eventually increase in the post-regulation period as future earnings information is better reflected in current prices. In summary, the effective regulation of misinformation results in a negative (positive) change in ERC (FERC) post-regulation.

However, regulators may fail to effectively improve the corporate information environment. First, as argued by Hayek (1945), regulators face inherent limitations in their information processing capacity, making it difficult to accurately judge misinformation. Consequently, their efforts may not only fail to curtail misinformation but also inadvertently suppress valid information. Additionally, regulators are vulnerable to the risk of regulatory capture (e.g., Stigler, 1971; Laffont and Tirole, 1991), which reduces their motivation to engage in market information governance. Firms can influence regulators through lobbying or bribery, steering regulatory actions away from investor interest - the maximization of shareholder value (Levine and Forrence, 1990). In such instances, regulators may act in favor of firms, deviating from optimal regulatory objectives. For example, they might suppress negative content in collusion with firms, regardless of whether the content is misinformation or not. As a result, the misinformation regulation may become ineffective, leading to unintended negative capital market consequences (see Figure 1b. Ineffective regulation). In this scenario, the corporate information environment may fail to improve or even deteriorate, which creates greater friction in valid information acquisition before EA. Consequently, this leads to stronger short-term market reactions to EA post-regulation because credible information is disclosed in EA, and there will be market adjustments to correct prior mispricing. Therefore, the ERC should be much higher post-regulation than that in the pre-regulation period, which means a positive change in ERC post-regulation. Similarly, the deterioration of the corporate information environment post-regulation increases uncertainty, making current prices less reflective of future earnings fundamentals. Consequently, FERC is lower in the post-regulation period compared to the pre-regulation period.

Given the numerous possibilities in our analysis, the impact of misinformation regulation on ERC and FERC remains unclear ex-ante. Therefore, we predict Hypothesis 3 in the null form:

H3a: The misinformation regulation does not affect ERC.

H3b: The misinformation regulation does not affect FERC.

3. Institutional Setting, Data, and Main Variables

3.1 Qinglang Operation for Business Environment

We utilize a unique setting of social media censorship in China, Qinglang Operation, to test our hypotheses. The Chinese government initiated the Qinglang Operation in 2016, led by the Cyberspace Administration of China, to manage and oversee the online environment. Each Qinglang Operation aims to address some specific types of inappropriate online phenomena and lasts several months. As shown in Appendix A.1, before 2023, previous Qinglang Operations focused on broad issues such as online vulgarity, privacy violations, and entertainment industry scandals. In contrast, the 2023 Qinglang Operation is the first formal regulation focused on online misinformation regarding the corporate online information environment. The 2023 Qinglang Operation was triggered by downward shift in economy and a spate of high-profile negative posts targeting entrepreneurs. The economic downturn intensified social pressures, leading to an increase in stigmatizing attacks and defamatory narratives against entrepreneurs and corporate images online. Following the end of strict epidemic lockdowns and facing severe economic downturns, the Chinese government has intensified efforts through this operation to improve business environment and stimulate economic recovery. During this period, the central and local Cyberspace Administrations enforced strict censorship of online misinformation regarding firms (especially negative ones, according to official documents). This provides a unique setting to examine the effectiveness of government's regulation of misinformation in digital space.

Two special actions under the 2023 Qinglang Operation significantly affect finfluencers' behavior on social media, and may consequently make a difference in capital markets. The first is

"Qinglang Operation: rectifying we-media chaos"[4] (hereafter, Qinglang-we-media), and the second is "Qinglang Operation: optimizing the business online environment and protecting the legitimate rights and interests of corporates"[5] (hereafter, Qinglang-business).

The Qinglang-we-media operation was enforced from March 2nd to early May 2023, which significantly affects finfluencers' behavior through stringent governance of finfluencers. This operation targets we-media entities who spread fabrication and dissemination rumors. Additionally, on March 28, 2023, the central Cyberspace Administration announced the Qinglang-business. This operation targets online misinformation against firms and entrepreneurs, including practices such as tarnishing corporate image, maliciously attacking firms via collecting negative information, disseminating adverse fake reports, and spreading false and misleading information. On April 24th, the central Cyberspace Administration formally required the local Cyberspace Administration to enforce Qinglang-business operation over the following three months, lasting until the end of July. As these two special actions overlap in both timing and policy targets, we have combined them under the term "Qinglang Operation," which spans from March 2nd to the end of July 2023 (see Appendix A.2 for the details of Qinglang Operation timeline).

While the central government officially declared that the Qinglang Operation would run from March 2nd to the end of July 2023, many local cyberspace administrations continued enforcing online regulations beyond this period. For example, the Shanghai government extended this policy through October, continuing its regulation of online misinformation with a particular focus on platforms such as Eastmoney Guba[6]. As for other local governments, it is likely that they will continue their censorship efforts, even without making public disclosures. Consequently, it is reasonable to expect the 2023 Qinglang Operation to maintain its influence on Chinese cyberspace, potentially extending beyond its official conclusion in July 2023. Anecdotal evidence has

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[4] Qinglang Operation: rectifying self-media chaos, available at: Link
[5] Qinglang Operation: optimizing the business online environment and protecting the legitimate rights and interests of corporates, available at: Link
[6] Shanghai Yangpu District Government Website, available at: Link

underscored the power of 2023 Qinglang Operation. Official reports indicate that by the end of July 2023, over 86,000 instances of misinformation had been censored and removed, and over 8,000 accounts across various social media platforms had been permanently deleted.[7] In our sample, we observe 4,649 records of account deletions on Eastmoney Guba from March to the end of July 2023.

3.2 Data

We use three datasets in this research: discussion-post dataset, user-profile dataset, and firm-relevant financial data. The firm-relevant financial data is obtained from the Chinese Stock Market and Accounting Research (CSMAR) Database, while other datasets are extracted from the Eastmoney Guba platform. To ensure sufficient data for analyzing changes in user behavior on social media, the finalized sample period begins on January 1, 2022.

Specifically, the discussion-post dataset is built upon posts from each Guba stock message board, including post-level attributes such as the post title, author, and URL. The raw data includes sample period from January 1, 2017, to November 21, 2023. For our research purpose, we retain posts from January 1, 2022, to the end of November 2023, which is the finalized discussion-post dataset.

Moreover, we collected user profile data in four rounds[8] to construct a user-profile dataset, which includes user characteristics such as the number of followers, following users, influence level, IP address, etc. The raw data covers users who posted at least once from January 1, 2017, to November 21, 2023 (limited by Guba website's anti-crawler, we cannot collect user profile data since 2024, and the last collection was in November 2023). We identify deleted accounts according to the username and estimate their deregistration timing using the date of their last posting activity on Guba, including all posts in individual Guba blog ("财富号") and stock message boards. We then assign the last post's date for each deleted user as their deregistration timing.

[7] Qinglang Operation typical instance, available at: Link
[8] We collected user profile data on July 1, Sept. 11, Oct. 18, and Nov. 15, 2023, respectively.

Finally, we exclude users deleted before January 1, 2022, and those registered after January 1, 2022. This ensures that we can observe complete user behavior throughout the entire sample period while also avoiding the issue of some late-registered users whose behavior is only observable after the implementation of the regulation. Only the latest crawled user profile observation for each unique user is retained to finalize the user-profile dataset (see Table 1 for details). Thus, the finalized user-profile dataset includes users who posted at least once after January 1, 2017, and were registered before January 1, 2022. As for the retained deleted users in the dataset, they were deregistered after January 1, 2022.

3.3 Identification of Finfluencers and Active Regular Users

To test our hypothesis, we identify the finfluencers and active regular users on Guba platform. Finfluencers are influential users who exert the power to affect investment decisions by actively creating posts to disseminate information on social media. Regular users are defined as frequent posters with no significant influence on the community.

First, we combine all collected users into a single sample. Within this sample, we identify finfluencers and active regular users based on user characteristics such as user profile visits, follower counts, and so on. Finally, we categorize within groups into deleted and non-deleted users. The use of consistent screening criteria during this process ensures comparability across these groups. Figure 2 shows the details of this process. The initial user sample includes users who posted at least once from January 1, 2017, to November 21, 2023, and were registered before January 1, 2022. The retained deleted users in the dataset were deregistered after January 1, 2022. Please refer to Appendix B and Table 2 for the details about our identification process.

3.4 Main Variables

3.4.1 Earnings Announcement in China

The Chinese market shares similarities with the U.S. in terms of corporate disclosure practices. In China, public firms are mandated to disclose their quarterly and annual report for relevant financial performance (i.e., 10-Q and 10-K forms in the U.S.), which are all audited.

However, the earnings announcement ("业绩快报" in Chinese, or "preliminary earnings estimate" in English) is a non-audited disclosure that firms can voluntarily release before the formal quarterly and annual report[9].

3.4.2 Relative Sentiment (Rsent)

Relative sentiment ($RSent_{j,m}$) measures the overall sentiment of user j's posts in month m, which is calculated as follows with values ranging from -0.5 to 0.5. 0 is relatively neutral, and 0.5/-0.5 is the most positive/negative sentiment, respectively. We assign neutral sentiment (i.e., 0) if user j does not post in month m:

$$RSent_{j,m} = \frac{1}{|P_{j,m}|} \sum_{p \in P_{j,m}} Sentiment_p$$

Where $Sentiment_p$ is the sentiment of post p. We use the fine-tuned Natural Language Processing (NLP) tool, fine-tuned FinBert, to score the $Sentiment_p$, ranging from -0.5 to 0.5 where -0.5 (0.5) represents the most negative (positive) sentiment. The fine-tuned FinBert model was trained on 5 Chinese text sentiment classification datasets. JD full, JD binary, and Dianping datasets consist of user reviews of different sentiment polarities. Ifeng and Chinanews consist of first paragraphs of news articles of different topic classes. $P_{j,m}$ is the set of all posts published by user j in month m, and the $|\cdot|$ operator counts the number of posts in such set.

3.4.3 Cumulative Abnormal Returns (CAR)

$CAR_{i,q[-3,n]}$ is the cumulative abnormal returns for firm i during the period from three-trading-days before to n-trading-days after the release date of the quarterly/annual report for fiscal quarter q. To account for potential information leakage, we include returns from three days before the release of the report. For firms with EA disclosure, earnings information is made available in corresponding non-audited EA and audited quarterly/annual report. In this case, $CAR_{i,q[-3,n]}$ is

[9]Shenzhen Stock Exchange, available at: Link

calculated as the sum of $CAR_{i,q[-3,n]}$ around the EA release and $CAR_{i,q[-3,n]}$ around the release of the corresponding quarterly/annual report. For firms without EA disclosure, $CAR_{i,q[-3,n]}$ is calculated around the release of the corresponding quarterly/annual report.

We calculate CAR using a two-step process. First, we estimate Capital Asset Pricing Model (CAPM) for each firm over an estimation window $[-45, -15]$ relative to the release date (EA date or quarterly/annual report date). CAPM coefficients are derived through regression, and expected returns are calculated for the event window. Finally, abnormal returns (AR) are the difference between actual and expected returns during the event window, and CAR is the sum of ARs over the window, measuring the firm's abnormal stock performance around the event date.

3.4.4 Unexpected Earnings (UE)

We use the seasonal random walk model to measure unexpected earnings because 1) analyst forecasts may be influenced by the regulation and 2) the Chinese analysts seldom issue their forecasts on quarterly EPS. Livnat and Mendenhall (2006) noted time-series earnings changes and analyst consensus forecasts yield similar estimates. Thus, we calculate $UE_{i,q}$ as previous studies (Chan et al., 1996; Liu et al., 2023):

$$UE_{i,q} = \frac{EPS_{i,q} - EPS_{i,q-4}}{p_{i,q}}$$

Where $EPS_{i,q}$ is the reported EPS for firm i in the quarterly/annual report for fiscal quarter q, and $EPS_{i,q-4}$ is the four-quarters-prior EPS for firm i. $p_{i,q}$ is the end-of-fiscal-quarter stock price for firm i in the fiscal quarter q.

4. Sample Selection and Empirical Specifications

We examine Hypothesis 1 using an approach similar to Mayzlin et al. (2014), which is suggested to interpret as statistical correlation. For Hypotheses 2 and 3, we rely on the Difference-in-differences (diff-in-diffs) framework, in which we interpret our results as causal impact.

The testing sample varies among hypotheses. Collectively, the sample period begins on January 1, 2022, to avoid the confounding factors of the early COVID-19 pandemic while keeping sufficient observations for analysis. For H1 and H2, the finalized sample is from January 1, 2022, to November 21, 2023[10]. The financial data from CSMAR for H3 regarding capital market reactions is from January 1, 2022, to the end of April 2024. Therefore, we have a symmetry sample period for pre-regulation (January 1, 2022, to the end of February 2023, 14 months) and post-regulation (March 1, 2023, to the end of April 2024, 14 months).

4.1 Validating the Misinformation Regulation Shock

First, we validate the underlying assumption for hypotheses. That is, the misinformation regulation shock indeed affects the account deletion and mainly targets finfluencers instead of active regular users. Eventually, regulators can intervene in capital markets through the regulatory effects on finfluencers' behavior. We examine and concrete this assumption through the difference between the number of deleted finfluencers and deleted active regular users post-regulation.

4.1.1 Sample Selection

We use user-profile dataset to validate the misinformation regulation shock. We identify all deleted finfluencers and active regular users based on the process in section 3.3 (see Appendix B for the details), who were registered before January 1, 2022, and deleted after January 1, 2022. Next, we count the number of monthly deleted finfluencers and active regular users over the period from January 2022 to November 2023.

4.1.2 Model Specification

Our design is akin to Mayzlin et al. (2014). However, it is important to note that this is not a diff-in-diffs estimator. This analysis is intended solely to illustrate the general trend of finfluencers' deletion compared to that of active regular users, without making any causal claims:

$$\#deleted\ KOLs_m - \#deleted\ regular\ users_m = \beta_0 + \beta_1 Post_m + \beta_2 IP_m + \varepsilon_m \quad (1)$$

[10] As mentioned in Section 3.2, Guba's anti-crawler does not allow to collect since 2024, and our final collection for user profile data was in November 2023

$\# \, deleted \, KOLs_m$ is the number of identified deleted finfluencers in month m, and $\# \, deleted \, regular \, users_m$ is the number of identified deleted active regular users in month m. As discussed in section 3.1, since the misinformation regulation was implemented since March 2, 2023, and remained in effect for an extended period even beyond July 2023, $Post_m$ equals 1 since March 1, 2023, otherwise 0. Additionally, we control a potential confounder in the sample period - *Provisions on the Management of Internet User Account Information*. This regulation was enforced starting August 1, 2022, mandating the disclosure of user's IP address. Thus, we introduce IP_m to isolate the impact of mandatory IP disclosure on users' behavior, assigning a value of 1 since August 1, 2022, and otherwise 0. The model (1) is estimated using time-series OLS, and heteroscedasticity-consistent standard errors are used (White, 1980).

We predict a positive β_1 as the misinformation regulation should lead to a significant increase in finfluencers' deletion relative to active regular users.

4.2 Hypothesis 1

4.2.1 Sample Selection

Figure 3 shows the sample selection process for examining H1, for which we construct pre- and post-regulation samples separately. The pre-regulation sample includes finfluencers deleted between March 1, 2022, and the end of November 2022, as well as other finfluencers who were still active during this period. The post-regulation sample includes finfluencers deleted between March 1, 2023, and the end of November 2023, as well as other finfluencers who were still active during the same period. For each sample, we report the descriptive statistics in Table 4 Panel A.

4.2.2 Model Specification

We first investigate the relationship between finfluencers' behavior and the likelihood of being deleted in pre-regulation period. To do so, we estimate model (2.1):

$$Del\_KOL_{j,pre} = \beta_0 + \beta_1 Avg\_Rsent_{j,pre} + \beta_2 Star\_kol_{j,pre} + \varepsilon_j \quad (2.1)$$

Where $Del\_KOL_{j,pre}$ is an indicator variable, identifying whether the finfluencer j was deleted between March 1, 2022, and the end of November 2022 in the pre-regulation sample. $Avg\_Rsent_{j,pre}$ is finfluencer j's average relative sentiment calculated by averaging the sentiment scores of all j's posts in January and February 2022, and 0 if user j do not post during pre-regulation period. Also, since KOLs with more influence are more likely to be targeted by regulators for deletion, we add $Star\_kol_j$ to control KOLs' influence, which is an indicator variable equals to 1 if finfluencer j's influence index ($Star_j$) is greater than the median of that in pre-regulation sample, otherwise 0.

Next, we estimate the correlation between finfluencers' behavior and the likelihood of being deleted in post-regulation period, for which we estimate model (2.2):

$$Del\_KOL_{j,post} = \beta_0{}' + \beta_1{}'Avg\_Rsent_{j,post} + \beta_2{}'Star\_kol_{j,post} + \varepsilon_j{}' \quad (2.2)$$

Where $Del\_KOL_{j,post}$ is an indicator variable, identifying whether the finfluencer j was deleted between March 1, 2023, and the end of November 2023 in the post-regulation sample. $Avg\_Rsent_{j,post}$ is finfluencer j's average relative sentiment calculated by averaging the sentiment scores of all j's posts in January and February 2023, and 0 if user j do not post during post-regulation period. Also, we add $Star\_kol_{j,post}$ to control KOLs' influence.

Our focus lies in the difference between β_1 and $\beta_1{}'$, which captures the change in the relationship between finfluencers' tones and the likelihood of being targeted for deletion before and after the misinformation regulation.

4.3 Hypothesis 2

4.3.1 Sample Selection

The testing sample for H2 includes identified non-deleted finfluencers and active regular users since January 1, 2022. Additionally, all of them were registered before January 1, 2022, to ensure we can observe the consecutive change in their posting behavior over time. We identify non-deleted finfluencers and active regular users based on the process detailed in section 3.3. The sample period is from January 1, 2022, to the end of November 2023, with summary statistics reported in Table 4 Panel B.

4.3.2 Model Specification

We identify non-deleted active regular users as a comparable benchmark for non-deleted finfluencers because the regulatory attention mainly focuses on finfluencers and is less likely to affect active regular users. Based on this, we estimate the regulatory effects by comparing changes in posting behavior between non-deleted finfluencers (treated group) and active regular users (control group) post-regulation, estimated as follows:

$$Outcome_{j,m} = \beta_0 + \beta_1 KOL_j * Post_m + \theta_m + \gamma_j + \varepsilon_{j,m} \quad (3)$$

$Outcome_{j,m}$ are variables of our interest: $Rsent_{j,m}$ for sentiment intensity, $Ln(1 + Neg\_Article)_{j,m}$ for the number of negative posts, $Ln(1 + Pos\_Article)_{j,m}$ for the number of positive posts, and $Ln(1 + Articles)_{j,m}$ for the number of monthly posts (see Appendix D for definition). KOL_j is an indicator variable, equal 1 for non-deleted finfluencers and 0 for non-deleted active regular users. $Post_m$ equals 1 since March 1, 2023, as the misinformation regulation was implemented since March 2, 2023, and extended by local governments beyond July 2023, otherwise 0. θ_m and γ_j are fixed effects for calendar year-month and unique users. Heteroscedasticity-consistent standard errors are clustered at users' IP address (province) level. We cluster at IP address level because there may be correlation between behavior of individuals regulated by the same local governments, and a higher-level cluster is also more robust (Abadie et al., 2023).

4.4 Hypothesis 3

4.4.1 Sample Selection

We begin by identifying all Chinese listed firms available in the CSMAR database as of the end of July 2024. To ensure consistency, we establish a symmetric sample period covering the pre-regulation phase from January 1, 2022, to the end of February 2023, and the post-regulation phase from March 1, 2023, to the end of April 2024. This provides equal durations of 14 months for both the pre-regulation and post-regulation periods. Next, we apply a series of filters to refine the sample. First, we exclude firms that were listed after January 1, 2022, to ensure consistent observations for each firm throughout the sample period. Next, we remove firms that were undergoing an IPO at the time of data collection. We also exclude firms that were delisted before April 30, 2024. Subsequently, we restrict the sample to firms listed on the Shanghai and Shenzhen Stock Exchange A-shares. Finally, firms from the financial industry are excluded, in line with previous studies. For more details, please refer to Table 3 Panel A.

4.4.1.1 Identification Strategy

As Chinese regulators do not disclose their regulatory focus, it is challenging to precisely identify treated and control firms. While using observable account deletions post-regulation to determine treatment status may seem reasonable, identifying treatment based on a pre-regulation measure is less endogenous. This approach is justified because regulation may take effect by deleting KOLs' accounts and affecting non-deleted KOLs' posting behavior. Therefore, we propose an identification strategy based on the likelihood of being affected during the pre-regulation period to identify treated and control firms.

Xu (2021) highlights asymmetries in regulatory scrutiny, showing that negative information is more likely to be censored. Li et al. (2023) indicate that negative misinformation is significantly more prevalent than positive ones. Anecdotal evidence indicates that some short sellers mislead investors by hinting at significant stock price declines on social media.[11] This aligns with the regulatory emphasis on censoring negative messages. Consequently, firms with a higher presence of finfluencers who have more negative tone are more likely to be affected by misinformation regulations, as these negative-toned finfluencers become the primary targets of such scrutiny, thus being treated firms.

[11] U.S. Accuses Prominent Short Seller Andrew Left of Fraud, Wall Street Journal, available at: Link

To do so, we first identify finfluencers with more ex-ante negative tones among all active finfluencers pre-regulation. Specifically, we measure Avg_Rsent_{j,pre_shock} by calculating the mean of $RSent_{j,m}$ for finfluencer j from January 1, 2022, to the end of February 2023. Finfluencers from the bottom half of Ln_visit-weighted Avg_Rsent_{j,pre_shock} are defined as finfluencers with more ex-ante negative tones (the cut-off value is 0.00003082[12]), where we use Ln_visits as a weight to take the users' influence into account. Next, we count the number of these finfluencers on each firm's stock message board from January 1, 2022, to the end of March 2023. Finally, we rank firms according to this metric, defining the top half as treated firms ($Treat_i$ is 1, the cut-off value is 43) and the bottom half as control firms ($Treat_i$ is 0).

4.4.1.2 PSM for Endogeneity

We acknowledge the presence of confounding factors that may lead to self-selection bias in our identification of treated and control firms, which we address using PSM. We conduct a PSM based on firms' characteristics in pre-regulation period to prevent the assignment of treatment from being contaminated by post-regulation information.

Firms' exposure to misinformation regulation depends on certain characteristics and business performance pre-regulation. That is, firms' characteristics are endogenous determinants of being targeted by misleading finfluencers and thus being treated. For example, Xu (2021) finds that large and profitable firms are more likely to attract public attention and be targeted by misinformation. Furthermore, recent business performance matters as regulators may protect firms with low performance from misinformation. Based on this, we conduct one-to-one nearest-neighbor PSM without replacement using a 0.01 caliper as follows:

$$Treat_i = \beta_0 + \beta_1 Size_{i,2022} + \beta_2 Roa_{i,2022} + \beta_3 BM_{i,2022} + \varepsilon_i \quad (4)$$

12 Sentiment scores are relatively high in our sample, making a cut-off value close to zero already notably low. As shown in Table OA-1, the median sentiment score for posts is 0.486 during the pre-regulation period and 0.475 in the post-regulation period. This does not present a concern, as our analysis focuses on the ranking of sentiment rather than the absolute values.

Where $Treat_i$ indicates whether firm i is treated or control group based on section 4.4.1.1. $Size_{i,2022}$ is proxied by the log of total asset of firm i for fiscal year 2022. $BM_{i,2022}$ represents the book-to-market value of firm i for fiscal year 2022. $Roa_{i,2022}$ is the return on assets of firm i for fiscal year 2022. The sample after PSM is used to test H3, which we call PSM sample (see Table 3 Panel B).

4.4.2 Model Specification

We design diff-in-diffs estimator to capture the causal impact of misinformation regulation on ERC and FERC. Our test is based on PSM sample excluding 2022 4th quarter observations, for which we report the descriptive statistics in Table 4 Panel C.

The ERC and FERC results are not theoretically interpretable during fiscal quarters in which buy-and-hold returns and cumulative abnormal returns straddle the regulation shock date. As illustrated in Figure 4, the buy-and-hold returns for the 4th fiscal quarter of 2022 are realized before the regulation shock, while the cumulative abnormal returns for the same fiscal quarter are realized after the regulation. In such cases, the ERC results are contaminated by the regulation, whereas the FERC results remain unaffected. Consequently, joint inference based on ERC and FERC is not theoretically feasible for the policy evaluation, as the joint effects based on ERC and FERC are partially contaminated. To ensure that the ERC and FERC results are theoretically valid and interpretable, we exclude all 2022 4th quarter observations[13]. After that, we define $Post_{fqtr,q}$ to indicate whether ERC and FERC are affected by the misinformation regulation, which equals 1 if the misinformation regulation has been implemented in fiscal quarter q, otherwise 0.

4.4.2.1 Earnings Response Coefficients (ERC)

We first examine how the difference in short-term market reactions between treated and control firms changes post-regulation, focusing on how the difference in ERC between these treated and control firms changes over time.

[13] In our sample, we identify 2,230 straddled observations out of 2,232 observations in 2022 the 4th fiscal quarter.

$$CAR_{i,q[-3,n]} = \beta_0 + \beta_1 UE_{i,q} + \beta_2 Treat_i + \beta_3 (Treat_i * Post_{fqtr,q}) + \beta_4 (UE_{i,q} * Treat_i)$$
$$+ \beta_5 (UE_{i,q} * Post_{fqtr,q}) + \boldsymbol{\beta_6} (UE_{i,q} * Treat_i * Post_{fqtr,q})$$
$$+ \sum \varphi_n * Controls_{i,q} * UE_{i,q} + \sum \gamma_p * Psm\_Controls_{i,2022} + \eta_k + \tau_{fqtr}$$
$$+ \theta_m + \varepsilon_{i,q} \quad (5)$$

Where $CAR_{i,q[-3,n]}$ is the cumulative abnormal returns for firm i's earnings news in fiscal quarter q. $UE_{i,q}$ is unexpected earnings for firm i in fiscal quarter q. $Treat_i$ indicates whether firm i is treated or control group based on section 4.4.1.2. $Post_{fqtr,q}$ equals 1 if the regulation has been implemented during fiscal quarter q, otherwise 0. Furthermore, the treatment assignment is endogenously determined, and therefore, many determinants of being treated may also be determinants of the ERC. As suggested by Francis and Ke (2006), we allow the coefficient on $UE_{i,q}$ to vary with a set of determinants (denoted $Controls_{i,q}$). $Controls_{i,q}$ include fiscal quarter-level firm size ($Size_{i,q}$), book-to-market value ($BM_{i,q}$), return on assets ($Roa_{i,q}$), and an indicator variable for whether current earnings is loss ($Loss_{i,q}$). Additionally, we also add the fiscal year-level control variables used in PSM model (4), including $Size_{i,2022}$, $BM_{i,2022}$ and $Roa_{i,2022}$. η_k controls industry fixed effects to capture the industry-varying heterogeneity. τ_{fqtr} are fixed effects for fiscal quarter (1st, 2nd, 3rd quarterly report and annual report), account for differential market reactions to earnings news across different fiscal quarters (Mendenhall and Nichols, 1988). θ_m controls the time trends and confounding factors over time.

$\boldsymbol{\beta_6}$ is the variable of our interest, which measures the change in the degree to which prices respond to unexpected earnings post-regulation. A negative coefficient indicates that an additional unit of unexpected earnings results in lower short-term market reactions to EA. This is because the surprise was already impounded into prices before EA, suggesting that misinformation regulation effectively improves the corporate information environment and the market is more efficient.

4.4.2.2 Future Earnings Response Coefficients (FERC)

We next examine the change in the degree to which current prices reflect future earnings post-regulation, measured by the FERC. Following prior studies (Collins et al., 1994; Lundholm and Myers, 2002; Choi et al., 2011; Zhu, 2019), we estimate equation (6):

$$
\begin{aligned}
RET_{i,q} = {} & \beta_0 + \beta_1 Earn_{i,q-1} + \beta_2 Earn_{i,q} + \beta_3 Earn_{i,q+1} + \beta_4 Treat_i \\
& + \beta_5 (Treat_i * Post_{fqtr,q}) + \beta_6 (Earn_{i,q-1} * Treat_i) + \beta_7 (Earn_{i,q} * Treat_i) \\
& + \beta_8 (Earn_{i,q+1} * Treat_i) + \beta_9 (Earn_{i,q-1} * Post_{fqtr,q}) \\
& + \beta_{10} (Earn_{i,q} * Post_{fqtr,q}) + \beta_{11} (Earn_{i,q+1} * Post_{fqtr,q}) \\
& + \beta_{12} (Earn_{i,q-1} * Treat_i * Post_{fqtr,q}) + \beta_{13} (Earn_{i,q} * Treat_i * Post_{fqtr,q}) \\
& + \boldsymbol{\beta_{14}} (Earn_{i,q+1} * Treat_i * Post_{fqtr,q}) + \sum \varphi_n * Controls_{i,q} * Earn_{i,q+1} \\
& + \sum \gamma_p * Psm\_Controls_{i,2022} + \eta_k + \tau_{fqtr} + \theta_m + \varepsilon_{i,t} \quad (6)
\end{aligned}
$$

$RET_{i,q}$ is the realized buy-and-hold returns over the entire fiscal quarter q for firm i. $Earn_{i,q}$ is calculated as earnings for firm i in fiscal quarter q, scaled by market value at the end of fiscal quarter $q-1$. $Post_{fqtr,q}$ equals 1 if the regulation has been implemented during the fiscal quarter q, otherwise 0. Other variables are the same as those in estimate equation (5). Also, we allow the coefficient on $Earn_{i,q+1}$ to vary with a set of determinants ($Controls_{i,q}$). Moreover, we add the fiscal year-level control variables used in PSM model (4), including $Size_{i,2022}$, $BM_{i,2022}$ and $Roa_{i,2022}$. η_k, τ_{fqtr}, and θ_m are fixed effects for industry, fiscal quarter, and calendar year-month. For the details of variable definition, please refer to Appendix D.

$\boldsymbol{\beta_{14}}$ in equation (6) is the variable of interest, which captures the change in the degree to which current prices reflect future earnings post-regulation, i.e., the change in FERC post-regulation. A positive β_{14} represents the improvement in corporate information environment, making current prices reflect future earnings to a greater extent.

5. Sample Summary

5.1 User-level and Firm-level Sample Summary

We identify each type of user following the process outlined in Section 3.3. Ultimately, we identify 357 deleted finfluencers and 8,581 non-deleted finfluencers. For active regular users, we identify 277 deleted active regular users and 49,368 non-deleted active regular users. For the firm-level sample, we identify 1,189 treated firms and 1,189 matched control firms based on the method described in Section 4.4.1 and outlined in Table 3. These firms are used to test Hypothesis 3.

5.2 User-level Descriptive Statistics

Table OA-2 reveals that both deleted and non-deleted finfluencers maintain similar levels of influence and engagement, with median Star ratings between 3 and 3.5, and comparable metrics in Age, Followers, Visits, and post creation. In contrast, both deleted and non-deleted active regular users have significantly lower influence and engagement compared to finfluencers. Deleted (non-deleted) active regular users have an equal median Star rating of 2, a shorter platform age of 2.8 years (2.9 years), and other comparable metrics in platform engagement.

This highlights a clear divide in impact between regular users and finfluencers, regardless of deletion status. Finfluencers are more active and influential, and thus more likely to draw the attention of regulatory bodies due to their heightened visibility and impact. On the other hand, regular users, given their significantly lower engagement and influence, are less likely to be subject to regulatory scrutiny, as the costs of overseeing these nobodies would far outweigh the benefits.

5.3 Firm-level Descriptive Statistics

Table OA-3 outlines firm-level descriptive statistics, comparing treated and control firms before and after the misinformation regulation. Aside from the book-to-market (BM) ratio, there are no significant differences between treated and control firms in other PSM control variables, with these BM differences remaining post-regulation.

Treated firms show higher cumulative abnormal returns (CAR) in longer windows compared to controls pre-regulation, while treated firms experience consistently lower CAR post-regulation. For realized buy-and-hold returns (RET) during fiscal quarters, treated firms outperform controls pre-regulation, but this advantage diminishes after the regulation, with no significant outperformance observed. In terms of profitability, treated firms' earnings (Earn) and unexpected earnings (UE) decline relative to controls post-regulation.

6. Misinformation Regulation and Account Deletions

In this section, we show the empirical results for the relationship between misinformation regulation and account deletion. First, we validate the power of misinformation regulation shock. Then, we examine our Hypothesis 1.

6.1 Validating the Misinformation Regulation Shock

We first present the trend of account deletion for identified finfluencers and active regular users from January 2022 to November 2023. Figure OA-2 indicates an ever-increasing trend in the account deletions of finfluencer accounts, with a spike in September 2023. This is in line with the anecdotal evidence in section 3.1: while the central government officially declared that the Qinglang Operation would run from March 2nd to the end of July 2023, many local cyberspace administrations continued enforcing online regulations beyond this period. Qinglang Operation may continue to have a significant impact on the online environment even beyond its official conclusion in July 2023. For identified active regular users, there is volatility in relevant account deletion, but the upward trend is not significant.

To further validate the effects of misinformation regulation shock, we utilize a time-series regression to see whether the regulation significantly affects finfluencers' account deletion. We estimate equation (1) in section 4.1.2, and Table 5 summarizes the results. The point estimate in column (1) indicates that the enforcement of misinformation regulation is significantly associated with an increase in the number of deleted finfluencers, while column (2) does not identify the same pattern for deleted active regular users. Column (3) identifies the difference between deleted finfluencers and active regular users, which suggests that misinformation regulation primarily affects finfluencers instead of active regular users.

6.2 Finfluencers' Posting Behavior and Account Deletions

As discussed in hypothesis 1, regulators mainly target potential misinformation producers based on users' posting behavior. In this context, finfluencers with more negative tones are more likely to be targeted for deletions post-regulation. We estimate model specifications (2.1) and (2.2) in section 4.2.2 to examine hypothesis 1, where our interest is the difference in the relationship between account deletions and negative tones pre- and post-regulation.

As Table 6 shows, the point estimates in columns (1) and (2) reveal a notable shift in regulatory focus: in the pre-regulation period, negative tones are associated with the increased likelihood of finfluencers being deleted, but this is not significant under 99% confidence level. However, this relationship is more pronounced and significant (-2.044, $p<0.05$ versus -3.063, $p<0.01$) post-regulation. The difference in such a relationship between pre- and post-regulation periods (-1.019, $p<0.05$) is statistically significant, indicating that finfluencers with more negative tones are more likely to be targeted for deletions after the misinformation regulation.

Additionally, given the huge infrequency of finfluencers' deletions relative to non-deleted finfluencers, we use logistic regression for rare events to enhance the robustness of empirical inference. Specifically, we apply penalized maximum likelihood estimation to correct for bias (Firth, 1993; Heinze and Schemper, 2002). Across all specifications, we obtain consistent evidence as above: after the misinformation regulation, the relationship between negative tones and likelihood of finfluencers being deleted is significantly enhanced.

7. Misinformation Regulation and Non-deleted Finfluencers' Posting Behavior

In this section, we analyze the impact of misinformation regulation on non-deleted finfluencers' posting behavior (H2). Furthermore, we also examine the treatment effects heterogeneity across different users.

7.1 How Misinformation Regulation Reshapes Non-deleted Finfluencers' Posting Behavior

We analyze based on two observable dimensions of finfluencers' posting behavior: the sentiment of posts and the number of posts. For model specification, we employ the reduced form estimator in 4.3.2 to examine the effects of misinformation regulation on non-deleted finfluencers' posting behavior. Table 7 summarizes our empirical results.

The positive $KOL_j * Post_m$ (0.015, p<0.01) in column (1) shows that non-deleted finfluencers' sentiment is more positive relative to non-deleted active regular users post-regulation, which is consistent to deterrence hypothesis. That means non-deleted finfluencers may strategically post more positive content to survive post-regulation. Similarly, we find consistent changes in the number of negative posts in column (2). The negative coefficient (-0.011, p<0.01) indicates that the non-deleted finfluencers' negative posts decrease post-regulation. We follow Bellemare and Wichman (2020) to obtain a semi-elasticity interpretation. That is, compared to non-deleted active regular users, the number of non-deleted finfluencers' monthly negative posts decreases by 1.094%[14]. We also observe identical pattern for the number of positive posts and all posts. The estimates in columns (3) and (4) show significant declines in both the number of positive posts (-0.076, p<0.01) and all posts (-0.07, p<0.01) after the regulation. The semi-elasticity interpretation is, relative to non-deleted active regular users, the volume of non-deleted finfluencers' positive posts and all posts decreases by 7.318%[15] and 6.761%[16] after the regulation, respectively. Our empirical results are consistent with the deterrence hypothesis, indicating that non-deleted finfluencers may adopt strategic actions to avoid censorship and survive.

7.2 Treatment Effect Heterogeneity

Since the difference among individuals, we check the treatment effects heterogeneity of misinformation regulation. Our priori is that individuals who ex-ante infrequently post negative content might naturally be cautious and more sensitive or responsive to the regulation, which may lead to treatment effects heterogeneity across different users in their response to policy

[14] Semi-elasticity: $\exp(-0.011) - 1 = -1.094\%$
[15] Semi-elasticity: $\exp(-0.076) - 1 = -7.318\%$
[16] Semi-elasticity: $\exp(-0.070) - 1 = -6.761\%$

intervention. To examine this, we estimate quantile diff-in-diffs regressions based on the baseline results in section 7.1, as illustrated in Figure 5.

Figure 5 (a) shows that, compared to non-deleted active regular users, the positive change in non-deleted finfluencers' relative sentiment is significant post-regulation, especially for finfluencers with initially more positive sentiment. These ex-ante cautious finfluencers strategically adjust more post-regulation, aligning with our expectation that sensitive individuals would modify their behavior more substantially when faced with increased scrutiny.

Figure 5 (b) identifies the change in the number of negative posts across quantiles. We find that non-deleted finfluencers' negative posts significantly decrease post-regulation, with the most pronounced reduction among those who initially posted fewer negative posts. These cautious finfluencers, who post fewer negative posts ex-ante, may have felt more constrained post-regulation, and there are more declines in the number of their negative posts after the misinformation regulation.

Similarly, we find identical evidence from the number of positive posts and all posts as well. Figure 5 (c) shows the decline in the number of non-deleted finfluencers' positive content, which is particularly pronounced for those with fewer ex-ante positive content. Figure 5 (d) illustrates that, compared with those regular ones, the decrease in the number of non-deleted finfluencers' overall posts is significant, particularly for finfluencers with the initially lower number of posts.

8. Capital Market Effects of Misinformation Regulation

8.1 Capital Market Effects: Earnings Response Coefficients (ERC)

We estimate equation (5) to examine how misinformation regulation affects ERC. Table 8 indicates that, compared to control firms, policy-targeted firms experience significantly strong market reactions post-regulation.

The positive coefficients indicate an increased responsiveness of prices to unexpected earnings post-regulation. Ideally, if misinformation regulation effectively improves the corporate information environment, the ERC should decrease after regulation because earnings surprises have already been impounded into prices before the EA. However, the positive coefficients in our results suggest the opposite side – short-term market reactions to EA are stronger post-regulation. That means, the corporate information environment is not improved, and instead, it deteriorates after the misinformation regulation because the information is not efficiently revealed into prices before EA, even in the post-regulation period. Eventually, market participants have to adjust their information set through the public disclosure of EA to correct previous mispricing.

8.2 Capital Market Effects: Future Earnings Response Coefficients (FERC)

Next, we assess the effects of misinformation regulation on FERC by estimating the equation (6). Table 9 shows empirical results. In column (1), the test is based on the realized buy-and-hold market returns over the entire fiscal quarter, and we change to the proxy of market-adjusted realized buy-and-hold returns in column (2). The variable of interest is $Treat_i * Post_t * Earn_{i,t,q+1}$, which are all significantly negative for both columns (-0.555, p<0.05 and -0.560, p<0.05, respectively). That means, compared to control firms, policy-targeted firms' current prices are less reflective of future earnings news regarding fundamental information.

Invoking findings in section 8.1, the empirical results suggest identical evidence that regulators do not effectively manage misinformation by improving corporate information environment. Instead, the corporate information environment deteriorates post-regulation, reflected by stronger short-term market reactions to EA and poor informativeness of current prices for future earnings.

8.3 Robustness Test

Since the treatment assignment is not perfectly exogenous, our findings may suffer from the endogeneity issue. Although we have used PSM to enhance the comparability between treated and control groups, it may also fail to work given many unobservable confounding factors. In this case, the estimated causal coefficients are not interpretable and stable. Therefore, we conduct robustness tests to mitigate this concern.

8.3.1 Parallel Trends Assumption

The internal validity of diff-in-diffs design relies on the assumption that there are no differential trends pre-treatment among treated and control firms. A common way to gauge the plausibility of the parallel trends assumption is to check for the absence of statistically significant diverging trends before treatment. We provide two approaches for parallel trends assumption to guarantee the internal validity of our causal inference.

First, we plot the dynamic event-study diff-in-diffs estimates of the effects of misinformation regulation on ERC and FERC, along with 99% confidence intervals. We define relative time based on the fiscal quarter in which misinformation regulation was first implemented (0 represents 1st fiscal quarter of 2023, when the Qinglang Operation was first enacted). For the ERC model, we have five observed five fiscal quarters post-regulation (from Q1 2023 to Q1 2024). However, for the FERC model, we have only four observed quarters post-regulation, as future earnings data for Q1 2024 was unavailable at the time of data collection. Figure OA-3 confirms the absence of diverging trends pre-treatment for both ERC and FERC. Furthermore, it suggests evidence of dynamic treatment effects over time, with particularly strong effects in the initial periods following the treatment.

Second, we follow prior literature (Falato et al., 2021; Aghamolla and Thakor, 2022; Huang et al., 2023) to conduct a falsification test using pre-treatment sample. We re-estimate our main results using the sample of EA released during the two-year-ahead period before the implementation of the 2023 Qinglang Operation (i.e., from Jan. 1st, 2021, to the end of 2022). Using 2022 Q1 fiscal quarter, one fiscal year prior to the implementation of misinformation regulation, as the pseudo-treated timing, we re-run estimates based on model specifications (5) for ERC results and (6) for FERC results, respectively. Table OA-4 presents the placebo results for the ERC model in columns (1) and (2) and for the FERC model in columns (3) and (4). The coefficients on $Treat_i * Pseudo\_Post_{fqtr,q} * UE_{i,q}$ are statistically insignificant from zero with opposite sign relative to our main results. Similarly, the coefficients on $Treat_i *$

$Pseudo\_Post_{fqtr,q} * Earn_{i,q+1}$ are slightly negative yet statistically insignificant. Overall, our falsification test suggests no evidence of differential trends in the ERC and FERC among treated and control firms before the misinformation regulation.

8.3.2 Ex-post Verification of Treatment Assignment

In our design, treatment status is assigned based on the ex-ante likelihood of firms being affected by misinformation regulation. Since we can observe the deletion of finfluencers' accounts post-regulation, we use the observed outcomes for treated and control firms post-regulation to verify whether the treatment assignment based on metrics during the pre-regulation period is valid. Figure OA-4 reports the average number of firms' affiliated deleted finfluencers over time. Each firm's affiliated deleted finfluencers are those at least posted once in relevant firm's stock message board after January 1, 2022, to the end of February 2023. We indeed find that, relative to control firms, treated firms are significantly affected by misinformation regulation through the governance of their affiliated finfluencers. Overall, by using the observable policy treatment outcomes, we can confirm the validity of our ex-ante treatment assignment.

8.3.3 Placebo Test: Re-randomization Test

Furthermore, we run the Fisher's permutation test, also known as re-randomization test (Fisher et al., 1966; Anderson and Robinson, 2001), to assess whether our findings are driven by spurious correlations due to endogenous treatment assignment and treated timing. Based on model specifications (5) and (6), we consider two tests for treatment status and treated timing, respectively. First, we randomly reassign the treatment status to all firms while maintaining the distribution of treated timing. We then run the same regressions of specifications (5) and (6) to diagnose whether the results are driven by endogenous treatment assignment. Second, we randomly reassign the treated timing to all firms while maintaining the distribution of treatment status. After that, we also run the same regressions of specifications (5) and (6) to diagnose whether the results are driven by endogenous treated timing. Overall, our test shows that the main results are less likely to be driven by spurious correlations.

Figures OA-5 and OA-7 present the results of coefficient estimates under 2,000 iterations to test whether the results are driven by endogenous treatment assignment or endogenous treated timing. In Figure OA-5, the distribution of estimates based on randomly reassigned treatment status is akin to a normal distribution with a mean of zero. Also, we observe a similar zero-mean normal distribution of estimates based on randomly reassigned treated timing in Figure OA-7. The results indicate that there are no significant treatment effects based on randomly reassigned treated status or treated timing, in which the pseudo-estimates are far away from our estimates.

In Figures OA-6 and OA-8, we next check the distribution of t-values corresponding to the estimates in Figures OA-5 and OA-7, respectively. Both distributions display a zero-mean normal distribution of simulated t-values, indicating that most fail to reject the null hypothesis because the relevant P-values are not significant. Overall, the simulation results suggest that the treatment effects based on randomly assigned treated status or treated timing are unlikely to be statistically significant, even if the simulated treatment effects estimates are not zero.

8.3.4 Oster Test

The misinformation regulation shock is not perfectly exogenous and is driven by many factors, such as firms' characteristics. Although we use PSM to mitigate endogeneity, the confounders cannot be fully ruled out, as it is impossible to observe all endogenous determinants. This may finally cause the issue of omitted variables in the model specifications (5) and (6). To address this concern, we use the Oster (2019) test to assess the coefficient stability and the likelihood that the main results are driven by the selection of unobservables.

The Oster test is based on the intuition that omitted variable bias that arises from omitting controls from the regression is informative about the bias that arises from the omission of the unobserved factors. The test allows the estimation of $\hat{\delta}$, the ratio of selection on unobservables over selection on observables that would be necessary to explain away the results. Oster (2019) suggests a rule of thumb that the estimated coefficient could be considered stable if it would be driven to 0 only when the importance of unobservables exceeds that of observables (i.e., $\hat{\delta} > 1$).

Table OA-5 reports the results of the Oster test for our empirical findings. For ERC model specification, Panel A shows that all results pass the Oster test. Panel B reports the test results for FERC model, in which all estimated causal effects pass the Oster test as well. Overall, this test suggests that, for the issue of omitted variables to drive our results, the selection problem would have to be severe.

8.3.5 The Trade-offs between Generalizability and Causality

Additionally, we consider the trade-offs in interpreting our main results, particularly concerning generalizability and causality. While PSM can address endogeneity and lead to more precise causal inference, the "manipulation" inherent in PSM may reduce the external validity, making it more challenging to generalize our findings. For the main results, we prioritize precise causality by using a smaller and stricter PSM caliper (0.01). To assess the generalizability of our findings, we relax the PSM caliper and re-estimate the equations (5) and (6) under the caliper of 0.025. The findings remain consistent with the main results, only with slight changes in magnitude (untabulated). This consistency supports the generalizability of our findings and mitigates concerns of "manipulation" of PSM to some extent.

8.4 The Sensitivity to Negative Earnings Surprise

Our prior analysis indicates that the regulation is ineffective in enhancing the corporate information environment. A key concern is that regulators may be subject to regulatory capture (e.g., Stigler, 1971; Laffont and Tirole, 1991) instead of acting in the public interest (Levine and Forrence, 1990) when engaged in market information governance.

While the intended objective of regulators is to curtail negative misinformation rather than simply censoring unfavorable content, in practice, regulatory capture may lead to deviations from this optimal policy objective (e.g., Stigler, 1971; Laffont and Tirole, 1991). For instance, regulators, influenced by lobbying or political pressures, may shift their focus toward suppressing negative news about firms, regardless of whether the content is truly misinformation. In such cases, they may suppress all negative information to align with corporate interests, which will lead to heightened market reactions to negative earnings news.

To examine this, we estimate model specification (8) in Appendix C to assess the sensitivity of the ERC to contemporaneous negative earnings surprise. Similarly, we estimate specification (10) to analyze the sensitivity of the FERC to future negative earnings surprise. Detailed model specifications and interpretations are provided in Appendix C.

The empirical results are reported in Table 10. Columns (1) and (2) present results for the sensitivity of the ERC model to negative earnings surprise, and columns (3) and (4) report the sensitivity of the FERC model. Columns (1) and (2) indicate that misinformation regulation does not affect the short-term market reactions to EA for firms with positive earnings surprise ($Treat_i * Post_{fqtr,q} * UE_{i,q}$ is insignificant). However, the short-term market reactions to EA are stronger for firms experiencing contemporaneous negative earnings surprise ($Neg\_surprise_{i,q} * UE_{i,q} * Treat_i * Post_{fqtr,q}$ is significantly positive, p<0.01). This finding suggests that misinformation regulation fails to curtail negative misinformation and instead deteriorates the corporate information environment for firms with negative earnings surprise. Columns (3) and (4) present the results for FERC model. The baseline estimates for $Treat_i * Post_{fqtr,q} * Earn_{i,q+1}$ show declines in price informativeness reflecting future earnings news for firms experiencing future positive earnings surprise. But the moderator ($Neg\_surprise_{i,q+1} * Earn_{i,q+1} * Treat_i * Post_{fqtr,q}$) does not indicate that this deterioration is more pronounced for firms with future negative earnings surprise. In summary, the FERC model shows that misinformation regulation equally deteriorates price informativeness for all types of future earnings news.

Our results provide indirect evidence that misinformation regulation may not aim to improve overall market information but instead focuses on censoring and suppressing negative news. This suggests the possibility of regulatory capture (Stigler, 1971; Levine and Forrence, 1990; Laffont and Tirole, 1991). Overall, our findings align with the arguments of Stigler (1971) and

Hayek (1945) that governments are neither motivated nor competent to effectively regulate market information.

9. Conclusion

In this paper, we examine how misinformation regulation on social media shapes platform finfluencers' behavior and, in turn, results in capital market effects. We find that misinformation regulation significantly leads to more finfluencers' account deletion, particularly among those with more negative tones. Furthermore, the regulation also alters non-deleted finfluencers' behavior: the volume of all types of their posts declines, and their tones become more positive post-regulation. Finally, our empirical results provide evidence of ineffective regulation, failing to improve the corporate information environment: the short-term market reactions are stronger post-regulation, and current prices are less informative for future earnings news post-regulation.

Using the unique setting of censorship on social media in China, this research highlights the economic consequences of ineffective misinformation regulation. Our findings are pertinent to both practices regarding regulatory interventions in digital spaces and the academic debate on the feasibility of government interventions. First, to our knowledge, our study is the first to evaluate the impact of information control in digital spaces, offering insights into recent emergent events, such as the attempts to shut down social media platforms' servers during the GME and the recent legal controversy about online content moderation[17]. In addition, this research contributes to academic discussion as well. As Bradley et al. (2023) point to diminishing informativeness post-GME, our research assesses if regulatory intervention can enhance price informativeness against misinformation. More importantly, our findings add understanding to the enduring debate on whether governments are motivated and competent in costly governance of market information (Hayek, 1945; Stigler, 1971), cautioning the ever-present risk of regulatory capture even in digital eras (e.g., Stigler 1971; Laffont and Tirole, 1991).

[17] Supreme Court Avoids Final Decision on State Regulation of Social Media, The Wall Street Journal, available at: Link

In conclusion, our paper builds on the seminal discussion of Miller and Skinner (2015), further exploring how government interventions reshape the corporate information environment in the digital era. Nowadays, the advances in AI technologies have greatly lowered the cost of producing misinformation and changed the market information environment (Bertomeu et al., 2024). Effective regulatory measures are urgently needed to prevent social media from rumor mills and jeopardizing capital markets. While our findings may not be generalizable to global markets, they offer a unique perspective on how capital markets operate under stringent censorship in digital spaces.

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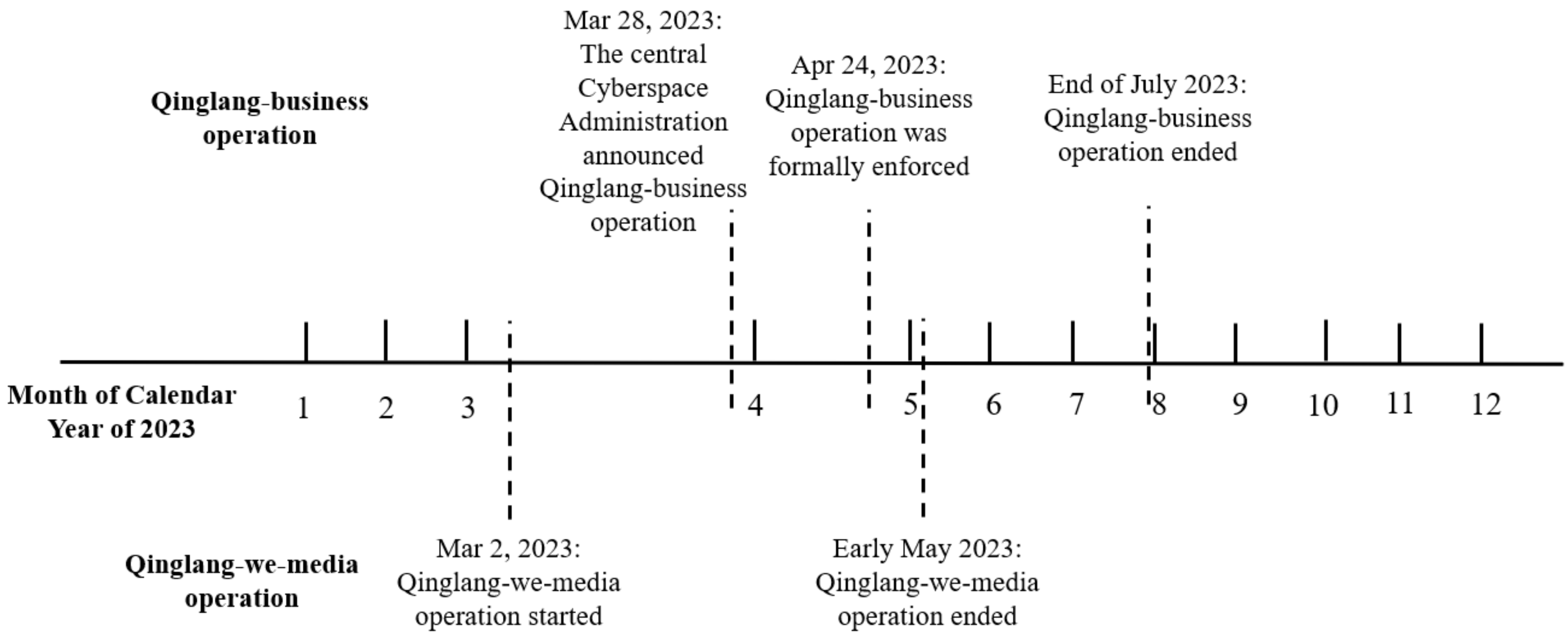
Appendix A: The Introduction to Qinglang Operation in China

Appendix A.1 The annual regulatory focus of the Qinglang Operation by year

Year	The regulatory focus of Qinglang Operation
2016	1. Minor's inappropriate App use: inappropriate advertisements and vulgar content related to pornography on minor's apps. 2. Regulate Website navigation: provision of navigation services to illegal websites. 3. Regulate unauthorized WeChat accounts: shut down accounts that disseminate obscene, pornographic content, false rumors, and violent or bloody material in violation of laws and regulations.
2017 – 2019	No official regulation.
2020	Targeted internet content: pornography, vulgarity, online violence, malicious marketing, and privacy violations.
2021	Focused on resolving scandals in the entertainment industry, including surrogacy controversies and fake entertainment gossip.
2022	1. Online live streaming: govern the disorder in the field of online live streaming and short video platforms. 2. Platform algorithms: comprehensive algorithm governance to address and rectify irregularities in application information services. 3. Traffic fraud: rectify the irregularities in MCN (Multi-Channel Network) agencies and prevent the manipulation of online traffic.
2023	1 Rectify "we-media" misconduct: curb illegal profit-making activities of 'we-media' and urge website platforms to establish comprehensive management for account registration, operation, and closure. 2 Regulate online business environment and protect corporate rights: thoroughly clean up and address false, misleading, and infringing information related to corporates and entrepreneurs. 3 Crackdown on manipulation of information content by water army: crackdown on the "water army" that manipulates content and regulates the information priority of traffic segments in the digital space. 4 Regulate on specific timing: 2023 Chinese spring festival and children's summer vacation: Protect children from illegal APPs.

Appendix A.2 The timeline of 2023 Qinglang Operation

This figure shows the timeline of 2023 Qinglang Operation enforcement. For Qinglang-business operation, the central Cyberspace Administration formally announced it on March 28, 2023, and enforced it through the local Cyberspace Administration on April 24, 2023. This operation lasted over the following three months and finally ended at the end of July 2023. For Qinglang-we-media operation, the central Cyberspace Administration formally enforced it on March 2, 2023. According to published documents, it lasted over the following two months and ended in early May 2023. Overall, the central government officially declared that Qinglang Operation was enforced from early March to the end of July 2023. However, the anecdotal evidence shows that Qinglang Operation may continue to have a significant impact on the online environment even beyond its official conclusion in July 2023.



Appendix B: Identification of Finfluencers and Active Regular Users

In this section, we outline the process used to identify finfluencers and active regular users. First, we combine all collected users into a single sample. Within this sample, we identify finfluencers and active regular users based on user characteristics, respectively. Finally, we categorize within groups into deleted and non-deleted users. The use of consistent screening criteria ensures comparability across these groups. Figure 2 describes the details of this process. The initial user sample includes users who posted at least once from January 1, 2017, to November 21, 2023, and were registered before January 1, 2022. The retained deleted users in the dataset were deregistered after January 1, 2022. For more details, please refer to Table 1.

B.1 Identification of Finfluencers

We begin by elaborating on the process of identifying finfluencers. Conceptually, finfluencers are influential users who exert the power to affect investment decisions by actively creating posts to disseminate information on social media. At the operational level, we identify finfluencers based on three factors: the number of user profile historical visits (hereafter, visits), the number of followers, and posting frequency. We acknowledge that variables - visits and the number of followers - may suffer from look-ahead bias since our data collection started after the implementation of the misinformation regulation. However, this concern is unlikely to significantly impact our analysis[1]. Furthermore, we place particular emphasis on visits as a key criterion since certain data - the number of followers - may be removed by Guba after a user deregisters. For example, in our sample, some deleted users with over 2,400,000 visits and 4,000 posts have 0 followers, which is clearly an anomaly. Therefore, we rely on visits to more accurately identify finfluencers.

Step 1: First, we filter out officially certified business entity accounts because our focus is individual finfluencer accounts. We obtain the filtered sample as subsample_1 for the next step.

Step 2: Then, we sort all users in subsample_1 into deciles based on visits. First, we select the top decile users, with a cut-off value of 2,396 visits. Then, we apply an additional filter (Filter 3), requiring a minimum of 10,000 visits, to create subsample_2 for the next step.

Step 3: Next, we apply a filter based on the number of followers. Campbell and Farrell (2020) define nano-finfluencers as users with at least 1,000 followers on Twitter. However, given the significant difference in user base size between Twitter and Guba (with Twitter's user base being over ten times larger), we adjust this threshold to 500 followers. Thus, we select users with more than 500 or deleted users with 0[2] followers (Filter 4) in subsample_2 as subsample_3 for the next step.

Step 4: We then set a threshold for posting frequency to confirm finfluencers. Users in subsample_3, who post, on average, at least once per week (Filter 5) are retained as the subsample_4 for the next step. Posting frequency is calculated by dividing the total number of

[1] Ideally, we should measure finfluencers' characteristics before January 1, 2022. However, given that the data collection occurred after the Qinglang Operation, we acknowledge the potential for look-ahead bias in our user profile data. However, this bias is minimal, as the report for each round of collection indicates that user characteristics on Guba are highly stable. For example, in the data review for the collection in Nov. 2023, the average monthly changes in followers per user is only -0.00004053, with the 99.9th percentile reaching a modest 14 changes in followers.

[2] As previously mentioned, Guba deletes data associated with deregistered users. Some of these users were highly influential before their deletion. Therefore, we retain observations of these deleted users who have significant influence but 0 followers.

posts by the total number of weeks since their registration, estimated based on 52 weeks per year.

Step 5: Lastly, we check subsample_4 users' posts and remove users without valid posts since January 1, 2022 (Filter 6). We define valid posts as those posts' titles are not "转发" ("repost" in English), null, or meaningless symbols (e.g., "#$%^&") because these posts do not have material expression for sentiment analysis. After that, we obtain the identified finfluencer sample and divide it into deleted and non-deleted finfluencers.

B.2 Identification of Active Regular Users

Furthermore, we identify regular users. Ideally, we aim to find those regular users who frequently post online but do not have significant influence on the community. We follow the procedures below to identify active regular users.

Step 1: We filter out officially certified business entity accounts first because our focus is individual finfluencer accounts. Through this, we obtain the subsample_1 for the next step.

Step 2: Then, we sort all users in subsample_1 into deciles based on visits. We select the bottom nine decile users (the cut-off value is 2,396) with less than 10,000 visits (Filter 1) as subsample_2 for the next step.

Step 3: After that, we use the threshold of nano-finfluencers and select users with less than 500 followers (Filter 2) in subsample_2 as subsample_3 for the next step.

Step 4: We then establish a threshold for posting frequency to identify active regular users. Users in subsample_3, who post, on average, at least once per week (Filter 5) are retained as the subsample_4 for the next step. Posting frequency is calculated by dividing the total number of posts by the total number of weeks since their registration, estimated based on 52 weeks per year.

Step 5: Lastly, we check subsample_4 users' posts and remove users without valid posts since January 1, 2022 (Filter 6). we define valid posts as those posts' titles are not "转发" ("repost" in English), null, or meaningless symbols (e.g., "#$%^&") because these posts do not have material expression for sentiment analysis. After that, we obtain the identified active regular user sample and divide it into deleted and non-deleted active regular users.

Appendix C: Model Specifications for Sensitivity to Negative Earnings Surprise

In this section, we elaborate on our model specifications for sensitivity to negative earnings surprise, as discussed in Section 8.3. We construct two separate specifications: one for the ERC and another for the FERC. For each, we begin with the basic ERC and FERC models and then extend them using the diff-in-diffs framework.

C.1 Test Sensitivity to Negative Earnings Surprise for ERC Model

We first specify the ERC model. The basic ERC model is presented in equation (7), where $\boldsymbol{\beta_1}$ captures the ERC for firms with positive earnings surprise, while $\boldsymbol{\beta_3}$ represents the moderating effect, which reflects the incremental changes in ERC for firms experiencing negative earnings surprise relative to those with positive earnings surprise. $Neg\_surprise_{i,q}$ is an indicator variable equals to 1 if $UE_{i,q}$ for firm i in fiscal quarter q is negative, otherwise 0.

$$CAR_{i,q[-3,n]} = \beta_0 + \boldsymbol{\beta_1} UE_{i,q} + \beta_2 Neg\_surprise_{i,q} + \boldsymbol{\beta_3}(Neg\_surprise_{i,q} * UE_{i,q}) \quad (7)$$

Next, we extend equation (7) using the diff-in-diffs framework to test our hypothesis. Specifically, we incorporate relevant two-way and three-way interaction terms to capture the ERC for firms with both positive and negative earnings surprise, as specified in equation (8). In this extended model, $\boldsymbol{\beta_6}$ represents the treatment effects on the ERC for firms with positive earnings surprise, while $\boldsymbol{\beta_{14}}$ captures the moderating effect for firms with negative earnings surprise, which we call the sensitivity to negative earnings surprise.

$$\begin{aligned} CAR_{i,q[-3,n]} = {} & \beta_0 + \beta_1 UE_{i,q} + \beta_2 Treat_i + \beta_3 (Treat_i * Post_{fqtr,q}) + \beta_4 (UE_{i,q} * Treat_i) \\ & + \beta_5 (UE_{i,q} * Post_{fqtr,q}) + \boldsymbol{\beta_6}(UE_{i,q} * Treat_i * Post_{fqtr,q}) + \beta_7 Neg\_surprise_{i,q} \\ & + \beta_8 (Neg\_surprise_{i,q} * UE_{i,q}) + \beta_9 (Neg\_surprise_{i,q} * Treat_i) \\ & + \beta_{10} (Neg\_surprise_{i,q} * Post_{fqtr,q}) \\ & + \beta_{11} (Neg\_surprise_{i,q} * Treat_i * Post_{fqtr,q}) \\ & + \beta_{12} (Neg\_surprise_{i,q} * UE_{i,q} * Treat_i) \\ & + \beta_{13} (Neg\_surprise_{i,q} * UE_{i,q} * Post_{fqtr,q}) \\ & + \boldsymbol{\beta_{14}} (Neg\_surprise_{i,q} * UE_{i,q} * Treat_i * Post_{fqtr,q}) \\ & + \sum \varphi_n * Controls_{i,q} * UE_{i,q} + \sum \gamma_p * Psm\_Controls_{i,2022} + \eta_k + \tau_{fqtr} + \theta_m \\ & + \varepsilon_{i,q} \quad (8) \end{aligned}$$

Ideally, if the misinformation regulation effectively targets negative misinformation, $\boldsymbol{\beta_6}$ should be zero (insignificant), and $\boldsymbol{\beta_{14}}$ should be significantly negative. This would indicate that the regulation does not affect firms with positive earnings surprise but improves the corporate information environment for those with negative earnings surprise.

However, if the misinformation regulation fails to curtail negative misinformation while not deteriorating the corporate information environment for firms with positive earnings surprise (insignificant $\boldsymbol{\beta_6}$), then $\boldsymbol{\beta_{14}}$ should be either zero (indicating no effects) or significantly positive (suggesting a worsening corporate information environment). In a more extreme scenario, if an ineffective misinformation regulation deteriorates the corporate information environment for all firms, $\boldsymbol{\beta_6}$ should be significantly positive as the baseline estimate. Meanwhile, $\boldsymbol{\beta_{14}}$ should either be insignificant (indicating that all firms experience the same degree of deterioration in the information environment) or significantly positive, suggesting that firms with negative earnings surprises face an even greater deterioration in their information environment.

C.2 Test Sensitivity to Negative Earnings Surprise for FERC Model

Next, we elaborate on the FERC model. The basic FERC model is specified in equation (9), where $\boldsymbol{\beta_3}$ captures the FERC for firms with positive earnings surprise. Additionally, $\boldsymbol{\beta_8}$ represents the moderating effect, reflecting the incremental changes in FERC for firms with negative earnings surprise relative to those with positive earnings surprise. $Neg\_surprise_{i,q}$ is an indicator variable equals to 1 if $UE_{i,q}$ for firm i in fiscal quarter q is negative, otherwise 0, and so forth, the same logic applies to $Neg\_surprise_{i,q-1}$ and $Neg\_surprise_{i,q+1}$.

$$\begin{aligned} RET_{i,q} = \beta_0 &+ \beta_1 Earn_{i,q-1} + \beta_2 Earn_{i,q} + \boldsymbol{\beta_3} Earn_{i,q+1} + \beta_4 Neg\_surprise_{i,q-1} \\ &+ \beta_5 Neg\_surprise_{i,q} + \beta_6 Neg\_surprise_{i,q+1} \\ &+ \beta_6 \left(Neg\_surprise_{i,q-1} * Earn_{i,q-1}\right) + \beta_7 \left(Neg\_surprise_{i,q} * Earn_{i,q}\right) \\ &+ \boldsymbol{\beta_8} \left(Neg\_surprise_{i,q+1} * Earn_{i,q+1}\right) \ (9) \end{aligned}$$

We extend equation (9) to align with the diff-in-diffs framework, as shown in the model specification (10). Specifically, we incorporate two-way and three-way interaction terms for three types of earnings: one-year-ahead earnings, current earnings, and future earnings.

$$\begin{aligned} RET_{i,q} = \beta_0 &+ \beta_1 Earn_{i,q-1} + \beta_2 Earn_{i,q} + \beta_3 Earn_{i,q+1} + \beta_4 Treat_i + \beta_5 \left(Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_6 \left(Earn_{i,q-1} * Treat_i\right) + \beta_7 \left(Earn_{i,q} * Treat_i\right) + \beta_8 \left(Earn_{i,q+1} * Treat_i\right) \\ &+ \beta_9 \left(Earn_{i,q-1} * Post_{fqtr,q}\right) + \beta_{10} \left(Earn_{i,q} * Post_{fqtr,q}\right) \\ &+ \beta_{11} \left(Earn_{i,q+1} * Post_{fqtr,q}\right) + \beta_{12} \left(Earn_{i,q-1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{13} \left(Earn_{i,q} * Treat_i * Post_{fqtr,q}\right) + \boldsymbol{\beta_{14}} \left(Earn_{i,q+1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{15} Neg\_surprise_{i,q-1} + \beta_{16} Neg\_surprise_{i,q} + \beta_{17} Neg\_surprise_{i,q+1} \\ &+ \beta_{18} \left(Neg\_surprise_{i,q-1} * Treat_i\right) + \beta_{19} \left(Neg\_surprise_{i,q} * Treat_i\right) \\ &+ \beta_{20} \left(Neg\_surprise_{i,q+1} * Treat_i\right) + \beta_{21} \left(Neg\_surprise_{i,q-1} * Post_{fqtr,q}\right) \\ &+ \beta_{22} \left(Neg\_surprise_{i,q} * Post_{fqtr,q}\right) + \beta_{23} \left(Neg\_surprise_{i,q+1} * Post_{fqtr,q}\right) \\ &+ \beta_{24} \left(Neg\_surprise_{i,q-1} * Earn_{i,q-1}\right) + \beta_{25} \left(Neg\_surprise_{i,q} * Earn_{i,q}\right) \\ &+ \beta_{26} \left(Neg\_surprise_{i,q+1} * Earn_{i,q+1}\right) \\ &+ \beta_{27} \left(Neg\_surprise_{i,q-1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{28} \left(Neg\_surprise_{i,q} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{29} \left(Neg\_surprise_{i,q+1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{30} \left(Neg\_surprise_{i,q-1} * Earn_{i,q-1} * Treat_i\right) \\ &+ \beta_{31} \left(Neg\_surprise_{i,q} * Earn_{i,q} * Treat_i\right) \\ &+ \beta_{32} \left(Neg\_surprise_{i,q+1} * Earn_{i,q+1} * Treat_i\right) \\ &+ \beta_{33} \left(Neg\_surprise_{i,q-1} * Earn_{i,q-1} * Post_{fqtr,q}\right) \\ &+ \beta_{34} \left(Neg\_surprise_{i,q} * Earn_{i,q} * Post_{fqtr,q}\right) \\ &+ \beta_{35} \left(Neg\_surprise_{i,q+1} * Earn_{i,q+1} * Post_{fqtr,q}\right) \\ &+ \beta_{36} \left(Neg\_surprise_{i,q-1} * Earn_{i,q-1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \beta_{37} \left(Neg\_surprise_{i,q} * Earn_{i,q} * Treat_i * Post_{fqtr,q}\right) \\ &+ \boldsymbol{\beta_{38}} \left(Neg\_surprise_{i,q+1} * Earn_{i,q+1} * Treat_i * Post_{fqtr,q}\right) \\ &+ \sum \varphi_n * Controls_{i,q} * Earn_{i,q+1} + \sum \gamma_p * Psm\_Controls_{i,2022} + \eta_k + \tau_{fqtr} \\ &+ \theta_m + \varepsilon_{i,t} \ (10) \end{aligned}$$

In this extended model, $\boldsymbol{\beta_{14}}$ represents the treatment effects on FERC for firms with positive earnings surprise, while $\boldsymbol{\beta_{38}}$ captures the moderating role of negative earnings surprise in the treatment effects on FERC, relative to firms with positive earnings surprise.

Ideally, if the regulation effectively targets negative misinformation, $\boldsymbol{\beta_{14}}$ should be insignificant zero, and $\boldsymbol{\beta_{38}}$ should be significantly positive. This would indicate that the regulation does not affect firms with positive future earnings surprise but improves the corporate information environment for those with negative future earnings surprise.

However, if the regulation fails to curtail negative misinformation while not deteriorating the corporate information environment for firms with positive earnings surprise (insignificant $\boldsymbol{\beta_{14}}$), then $\boldsymbol{\beta_{38}}$ should be either zero (indicating no effects) or significantly negative (suggesting a worsening corporate information environment). In a more extreme scenario, if an ineffective misinformation regulation deteriorates the corporate information environment for all firms, $\boldsymbol{\beta_{14}}$ should be significantly negative as the baseline estimate. Meanwhile, $\boldsymbol{\beta_{38}}$ should either be insignificant (indicating that all firms experience the same degree of deterioration in the information environment) or significantly negative, suggesting that firms with negative earnings surprises face an even greater deterioration in their information environment.

Appendix D: Variable Definition

Variable	Definition
Panel A: Post-level Measurement	
$Read_p$	Readership, which is the total historical number of individuals who have clicked and read the post p.
$Comment_p$	The total number of replies that the post p receives.
$Title\ Length_p$	The number of the Chinese characters in the post p's title.
$Sentiment_p$	The sentiment score of post p measured by fine-tuning FinBERT, ranging from -0.5 to 0.5 where -0.5 (0.5) represents the most negative (positive) sentiment. We use an open-source FinBert model, which was fine-tuned on five Chinese sentiment classification datasets: JD full, JD binary, and Dianping (user reviews), and Ifeng and Chinanews (news article intros).
Panel B: User-level Measurement	
$Star_j$	User j's influence index. The maximum rating is 5 stars, and the minimum rating is 0 stars, with increments of 0.5 stars.
Age_j	User j's Guba age, which is calculated from the date of registration, measured in years.
$Following_j$	The number of accounts followed by the user j.
$Follower_j$	The number of the user j's followers.
$Visit_j$	Total historical visits to user j's profile page.
Ln_visit_j	The natural log of total historical visits to user j's profile page.
All_posts_j	The number of all posts published by user j. If the number exceeds 50,000, it no longer records the exact number, only displaying 50,000.
$IP\_address_j$	The user j's IP address at provincial level for mainland China users and country

	level for foreign users (e.g., the U.S., Singapore).
$Reply_j$	The number of replies the user j writes. This number is calculated independently of the number of posts and does not include or overlap with it.
$Stock_j$	The number of stocks followed by the user j.
$Avg\_Rsent_{j,pre}$	Finfluencer j's average relative sentiment calculated by averaging the sentiment scores of all j's posts in January and February 2022. We assign relatively neutral (0) if user j do not post during pre-regulation period.
$Avg\_Rsent_{j,post}$	Finfluencer j's average relative sentiment calculated by averaging the sentiment scores of all j's posts in January and February 2023. We assign relatively neutral (0) if user j do not post during post-regulation period.
$Star\_kol_{j,pre}$	An indicator variable equals to 1 if finfluencer j's influence index ($Star_j$) is greater than the median of that in pre-regulation sample, otherwise 0.
$Star\_kol_{j,post}$	An indicator variable equals to 1 if finfluencer j's influence index ($Star_j$) is greater than the median of that in post-regulation sample, otherwise 0.
$Del\_KOL_{j,pre}$	Indicator variable equals to 1 if the finfluencer j was deleted between March 1, 2022, and the end of July 2022 in the pre-regulation period, otherwise 0.
$Del\_KOL_{j,post}$	An indicator variable equals to 1 if the finfluencer j was deleted between March 1, 2023, and the end of July 2023 in the post-regulation sample, otherwise 0.
$RSent_{j,m}$	Relative sentiment ($RSent_{j,m}$) is user j's monthly sentiment by averaging the sentiment scores of all j's posts in month m minus 0.5, calculated using fine-tuned FinBert. It is relatively neutral (0) if user j do not post during month m.
$Ln(1 + Articles)_{j,m}$	The natural log of one plus the number of user j's posts in month m.
$Ln(1 + Neg\_Article)_{j,m}$	The natural log of one plus number of posts with sentiment score below 0 made by user j in month m.

$Ln(1 + Pos\_Article)_{j,m}$	The natural log of one plus number of posts with sentiment score above 0 made by user j in month m.
Avg_Rsent_{j,pre_shock}	Finfluencer j's average relative sentiment calculated by calculating the mean of $RSent_{j,m}$ for finfluencer j from January 1, 2022, to the end of February 2023. We assign relatively neutral (0) if user j do not post during post-regulation period.
KOL_j	An indicator variable, which is equal 1 for non-deleted finfluencers and 0 for non-deleted active regular users.
Panel C: Firm-level Measurement	
$Size_{i,q}$	Firm size is calculated as the natural log of one plus total asset for firm i in fiscal quarter q.
$Roa_{i,q}$	The return on assets for firm i in fiscal quarter q.
$BM_{i,q}$	The book-to-market value for firm i in fiscal quarter q.
$Loss_{i,q}$	An indicator variable equals 1 if firm i's earnings in fiscal quarter q are loss, otherwise 0.
$CAR_{i,q[-3,n]}$	$CAR_{i,q[-3,n]}$ is the cumulative abnormal returns for firm i during the period from three-trading-days before to n-trading-days after the release date of earnings news for fiscal quarter q. To account for potential information leakage, we include returns from three days before the release of earnings news. For firms with EA disclosure, earnings information is made available in corresponding non-audited EA and audited quarterly/annual report. In this case, $CAR_{i,q[-3,n]}$ is calculated as the sum of $CAR_{i,q[-3,n]}$ around the EA release and $CAR_{i,q[-3,n]}$ around the release of the corresponding quarterly/annual report. For firms without EA disclosure, $CAR_{i,q[-3,n]}$ is calculated around the release of the corresponding quarterly/annual report. We calculate CAR using a two-

	step process. First, we estimate Capital Asset Pricing Model (CAPM) for each firm over an estimation window $[-45, -15]$ relative to the release date (EA date or quarterly/annual report date). CAPM coefficients are derived through regression, and expected returns are calculated for the event window. Finally, abnormal returns (AR) are the difference between actual and expected returns during the event window, and CAR is the sum of ARs over the window, measuring the firm's abnormal stock performance around the event date.
$RET_{i,q}$	$RET_{i,q}$ is the realized buy-and-hold returns over the fiscal quarter q for firm i, calculated from the end of fiscal quarter q-1 to the end of fiscal quarter q.
$RET\_Mkt\_Adj_{i,q}$	RET_Mkt_Adj is market-adjusted realized buy-and-hold returns, which is calculated as the difference between realized buy-and-hold returns over the entire fiscal quarter q for firm i and the realized buy-and-hold equal-weighted market returns over the entire fiscal quarter q.
$UE_{i,q}$	$UE_{i,q} = (EPS_{i,q} - EPS_{i,q-4})/p_{i,q}$, where $EPS_{i,q}$ is the reported EPS for firm i in the 10-Q/10-K for fiscal quarter q, and $EPS_{i,q-4}$ is the four-quarters-prior EPS for firm i. $p_{i,q}$ is the end-of-fiscal-quarter stock price for firm i in the fiscal quarter q.
$Earn_{i,q}$	$Earn_{i,t,q}$ is calculated as earnings from firm i's earnings announcement for fiscal quarter q, scaled by market value at the end of fiscal quarter q-1.
$Neg\_surprise_{i,q}$	An indicator variable equals to 1 if $UE_{i,q}$ for firm i in fiscal quarter q is negative, otherwise 0. As defined, $UE_{i,q}$ represents the unexpected earnings for firm i in fiscal quarter q, calculated as the difference between the EPS of the current fiscal quarter q and the EPS from the same fiscal quarter in the prior year.
Panel D: Other Variables	

$\# \, deleted \, KOLs_m$	The number of identified deleted finfluencers in month m.
$\# \, deleted \, regular \, users_m$	The number of identified deleted active regular users in month m.
$Post_m$	An indicator variable, equal to 1 since March 1, 2023, as Qinglang Operation (misinformation regulation) was implemented since March 2, 2023, otherwise 0.
$Post_{fqtr,q}$	An indicator variable is equal to 1 if the misinformation regulation has been implemented during the fiscal quarter q, otherwise 0.
$Treat_i$	An indicator variable is equal to 1 if the firm i is in treated group, other wise 0. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards in the pre-regulation period. To address the endogeneity issue, we then match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper.
$Pseudo\_Post_{fqtr,q}$	A pseudo policy-timing indicator for whether the misinformation regulation has been implemented. We designate the 1st fiscal quarter of 2022, one fiscal year prior to the implementation of misinformation regulation, as the pseudo-treated timing. The variable $Pseudo\_Post_{fqtr,q}$ is equal to 1 on and after the 2022 Q1, otherwise 0.

Figure 1

The Hypothesis 3 development

This figure demonstrates the development of hypothesis 3. The discussion is developed based on effective and ineffective government assumptions, respectively. The difference in ERC and FERC between pre- and post-regulation periods is our focus.

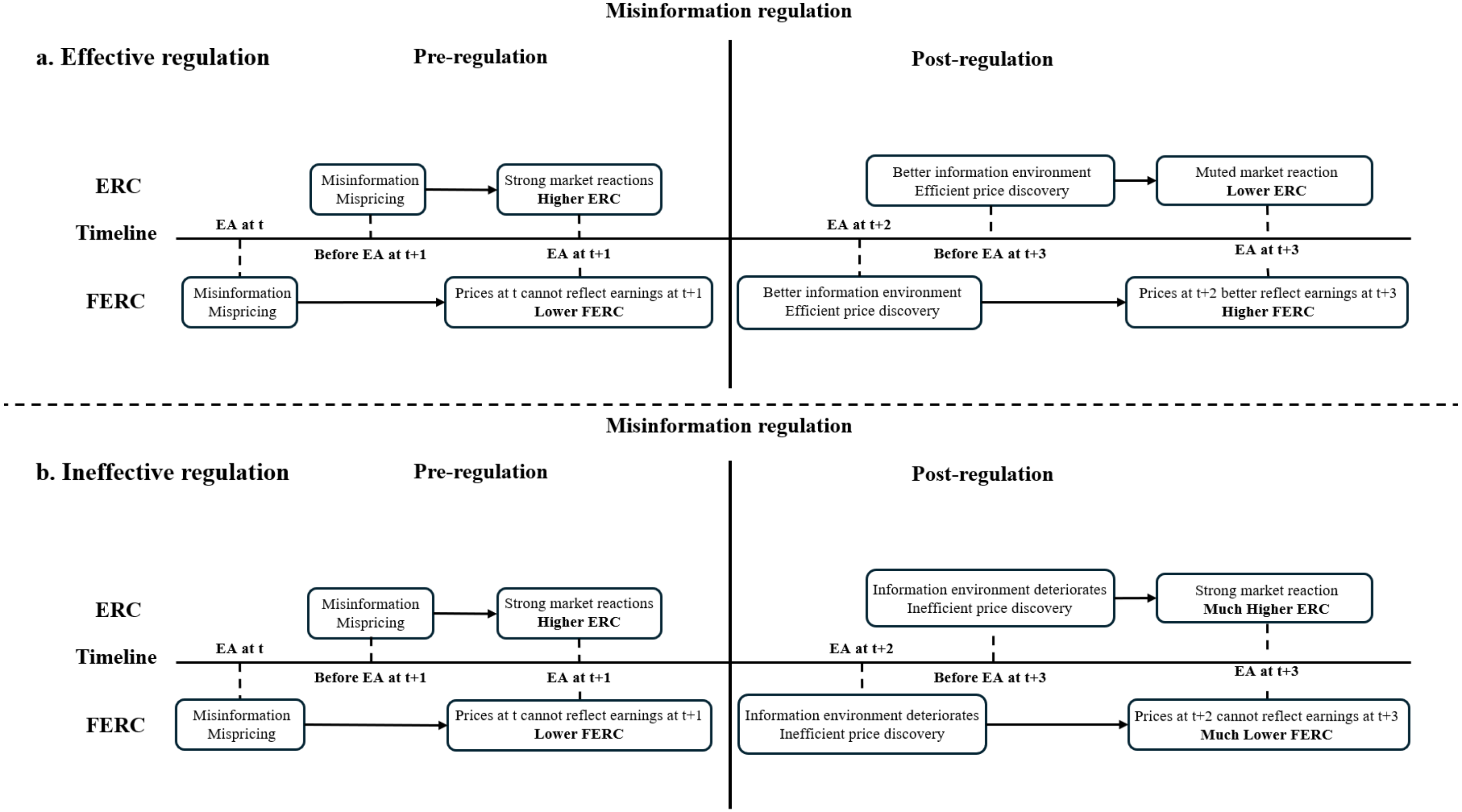


Figure 2

Identification of finfluencers and active regular users

This figure illustrates the process for identifying finfluencers and active regular users. First, we sort all users into deciles based on their historical visit data. From the top decile, we apply specific filters to identify the finfluencer sample. Similarly, for the bottom nine deciles, we use filters to identify the active regular user sample. Finally, identified finfluencer (active regular user) sample is then further divided into deleted and non-deleted finfluencer (active regular user) samples.

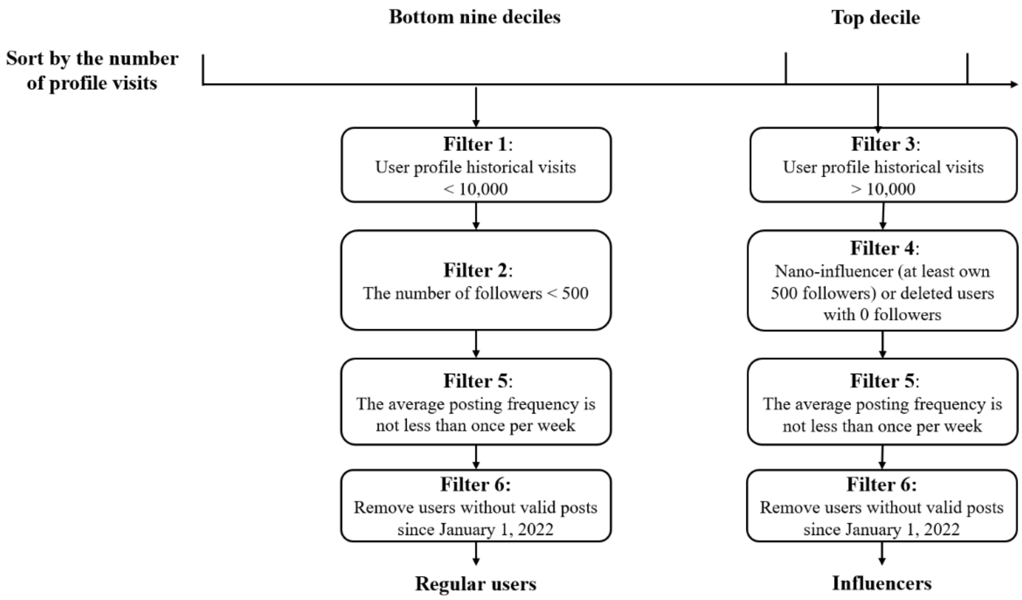


Figure 3

Sample selection for H1

This figure shows our sample selection process for examining H1, for which we construct pre- and post-regulation samples separately. The pre-regulation sample includes finfluencers deleted between March 1, 2022, and the end of November 2022, as well as other finfluencers who were still active during the same period. We construct $Del\_KOL_{j,pre}$ to identify these deleted finfluencers in pre-regulation sample, which equals to 1 if the finfluencer j is deleted in the pre-regulation sample, and 0 otherwise. The post-regulation sample includes finfluencers deleted between March 1, 2023, and the end of November 2023, as well as other finfluencers who were still active during the same period. We construct $Del\_KOL_{j,post}$ to identify these deleted finfluencers in post-regulation sample, which equals to 1 if the finfluencer j is deleted in the post-regulation sample, and 0 otherwise. We investigate the relationship between users' average relative sentiment and the likelihood of being deleted based on pre- and post-regulation samples, respectively, where the average relative sentiment is measured based on their posts' sentiment two months ahead (i.e., January and February 2022 for the pre-regulation sample, and January and February 2023 for the post-regulation sample).

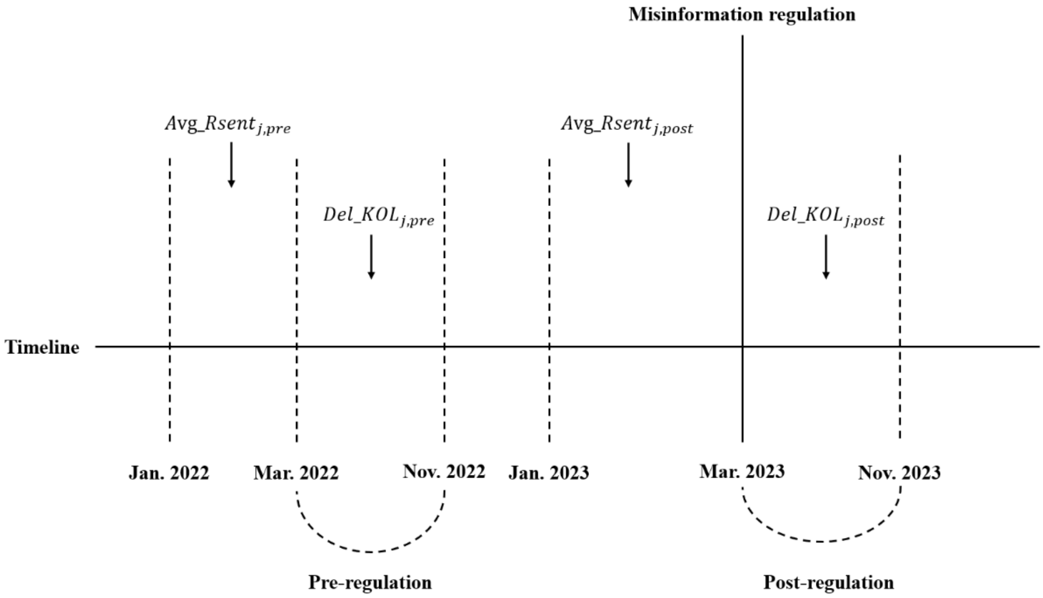


Figure 4

The straddled observations in 2022 4th fiscal quarter

This figure shows the straddled observations in 2022 4th fiscal quarter. We illustrate the situation in which buy-and-hold returns and cumulative abnormal returns following EA release for 2022 4th fiscal quarter straddle the regulation shock date. The buy-and-hold returns for the 4th fiscal quarter of 2022 are realized before the regulation shock, while the cumulative abnormal returns for the same fiscal quarter are realized after the regulation. In such cases, the ERC results are contaminated by the regulation, whereas the FERC results remain unaffected.

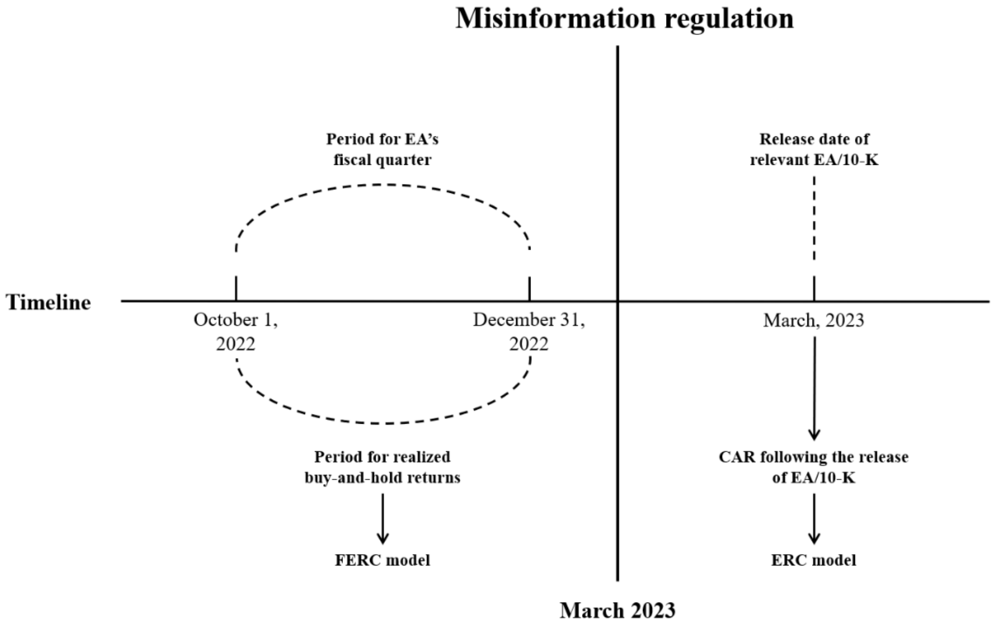


Figure 5

The treatment effects heterogeneity of misinformation regulation

This figure graphs quantile-regression diff-in-diffs estimates of the effects of misinformation regulation on non-deleted finfluencers' posting behavior. Relative sentiment ($RSent_{j,m}$) is user j's monthly relative sentiment by averaging the sentiment scores of their posts. $Ln(1 + Neg\_Article)_{j,m}$ proxies the number of negative posts, which is the natural log of one plus number of posts with sentiment score below 0 made by user j in month m. $Ln(1 + Pos\_Article)_{j,m}$ proxies the number of positive posts, which is the natural log of one plus number of posts with sentiment score above 0 made by user j in month m. $Ln(1 + Articles)_{j,m}$ proxies the number of overall posts, which is the natural log of one plus the number of user j's posts in month m. The treated group is non-deleted finfluencers, and control group is non-deleted active regular users. All specifications are estimated using OLS and include fixed effects for individual users and calendar year-month. The dashed lines represent 95% confidence intervals.

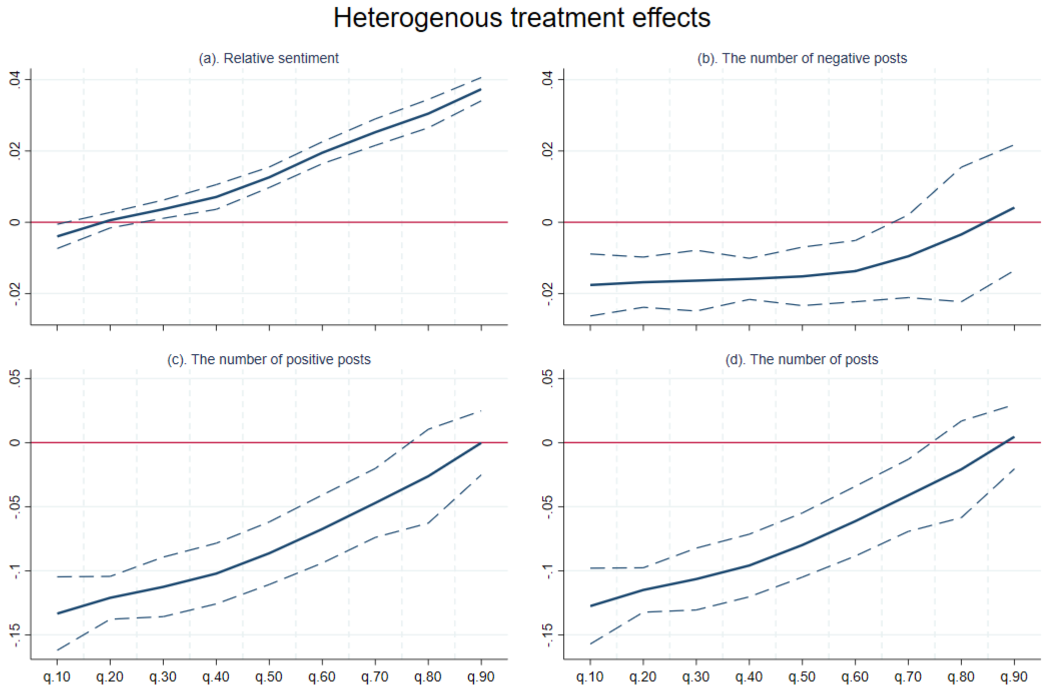


Table 1

User-profile dataset: deleted and non-deleted users

This table summarizes the user profile dataset. We collected user profile data for four rounds, which were conducted in July, September, August, and November 2023, respectively. We collected all user profile data of users who posted at least once from January 1, 2017, to November 21, 2023. To ensure we could observe consistent behavioral changes, we excluded users who registered after 2022. Additionally, we excluded users who were deleted before 2022, as they fall outside the sample period. For deleted users, we track the deleted date by last post's date. Two important disclosures help us estimate the deleted date: the last update date of caifuhao (财富号) and the last post's date. Based on these two, we match the last post's date with each deleted user, where the last post's date is the latest one among several available dates from the updated caifuhao and user post dataset. The number reported in above table is the number of unique users. For each unique deleted and non-deleted user, we only retain the observation from the most recent crawled dataset.

			Unique users
Panel A: Deleted users			
All deleted users			34,238
	Remove obs. who were deleted before 2022	(15,348)	
	Remove obs. who registered after 2022	(8,103)	
Deleted users in our sample			10,787
Panel B: Non-deleted users			
All non-deleted users			7,125,518
Identifying deregistration date by last post date:			
	Remove obs. who registered after 2022	(636,987)	
Non-deleted users in our sample			6,488,531

Table 2

Sample selection: identification of finfluencers and active regular users

This table reports the process of identifying deleted and non-deleted finfluencers, as well as active regular users. The selection follows the procedure as described in section 3.3. For the initial user sample, we collected all users who posted at least once from January 1, 2017, to November 21, 2023, please read Table 1 for details. The selection is mainly based on historical user profile visits (hereafter, visits), and then we conduct a series of filters to finally identify different types of users. The valid posts are defined as those posts' titles are not "转发" (in English, "Repost" or "Retweet") because these posts do not have material expression for sentiment analysis. Finally, for finfluencers, we identify 357 deleted finfluencers and 8,581 non-deleted finfluencers. For active regular users, we identify 277 deleted active regular users and 49,368 non-deleted active regular users, respectively.

			Unique Users
Panel A: Initial user sample			
	All deleted users	10,787	
	All non-deleted users	6,488,531	
All users in initial sample			6,499,318
Panel B: Identified finfluencers			
All users in initial sample			6,499,318
	Remove certified business entity accounts	(5,909)	
			6,493,409
Top decile's users based on visits (cut-off value: 2396)			649,498
	Filter 3 (historical profile visits > 10,000)	(437,593)	
	Filter 4 (Nano-finfluencer or deleted users whose follower data has been deleted by Guba)	(192,358)	
	Filter 5 (The average posting frequency is not less than once per week)	(7,852)	
	Fiter 6 (Remove users without valid posts since January 1, 2022)	(2,757)	
Identified Finfluencers			**8,938**

	Identified deleted finfluencers	**357**	
	Identified non-deleted finfluencers	**8,581**	
Panel C: Identified active regular users			
All users in initial sample			6,499,318
	Remove certified business entity accounts	(5,909)	
			6,493,409
Bottom nine deciles' users based on visits (cut-off value: 2396)			5,844,098
	Filter 1 (historical profile visits < 10,000)	(0)	
	Filter 2 (The number of followers < 500)	(1,388)	
	Filter 5 (The average posting frequency is not less than once per week)	(5,780,740)	
	Filter 6 (Remove users without valid posts since January 1, 2022)	(12,325)	
Identified active regular users			**49,645**
	Identified deleted active regular users	**277**	
	Identified non-deleted active regular users	**49,368**	

Table 3

Sample selection: Chinese listed firms

This table reports the sample selection of treated and control firms in our regression analysis. Panel A details the initial selection based on firms' characteristics. Then, we merge 3,016 firms with treatment indicator (we identify treatment indicator for 5,557 according to the number of finfluencers with more ex-ante negative tones on their stock message boards pre-regulation) and conduct nearest-neighbor propensity score matching using 0.01 caliper. Finally, we identified 1,189 treated firms and 1,189 control firms.

Panel A: Listed firms from CSMAR (collected from CSMAR on July 28, 2024)			
All unique firms			5,758
	Remove firms that were listed after January 1, 2022	(790)	
	Remove firms that are in IPO	(19)	
	Remove firms that were delisted before April 30, 2024	(279)	
	Remove non-Shanghai/Shenzhen stock exchange A-share firms	(1,612)	
	Remove firms in financial industry	(42)	
Listed firms for PSM			3,016
Panel B: Identification of treated and control firms after PSM			
	Treated firms	1,524	
	Control firms	1,492	
Selected firms for PSM			3,016
	Remove firms without matched counterfactuals	(632)	
	Remove firm without earnings disclosure data in CSMAR	(1)	
	Remove matched firm for 001914	(1)	
Sampled firms for causal inference			2,378
	Treated firms	1,189	
	Control firms	1,189	

Table 4

Summary statistics for testing sample

This table reports the descriptive statistics for the testing sample corresponding to each hypothesis. The sample in Panel A is used to test model specifications (2.1) and (2.2). The sample in Panel B is used for model specification (3), and the sample in Panel C is used for model specifications (5) and (6).

Variable	# obs.	Min	P10	p25	Median	p75	P90	Max	Mean	SD
Panel A: Testing sample for Hypothesis 1										
Pre-regulation sample:										
$Del\_KOL_{j,pre}$	8,935	0	0	0	0	0	0	1	0.005	0.072
$Avg\_Rsent_{j,pre}$	8,935	-0.178	0	0.0264	0.326	0.418	0.461	0.499	0.265	0.178
$Star\_kol_{j,pre}$	8,935	0	0	0	1	1	1	1	0.590	0.492
Post-regulation sample:										
$Del\_KOL_{j,post}$	8,833	0	0	0	0	0	0	1	0.029	0.166
$Avg\_Rsent_{j,post}$	8,833	-0.143	0	0	0.249	0.383	0.445	0.499	0.222	0.178
$Star\_kol_{j,post}$	8,833	0	0	0	1	1	1	1	0.630	0.483
Panel B: Testing sample for Hypothesis 2										
$RSent_{j,m}$	1,332,827	-0.304	0	0	0.181	0.380	0.479	0.500	0.192	0.197
$Ln(1 + Articles)_{j,m}$	1,332,827	0	0	0	0.693	1.946	2.890	9.686	1.111	1.235
$Ln(1 + Neg\_Article)_{j,m}$	1,332,827	0	0	0	0	0.693	1.099	7.121	0.274	0.546
$Ln(1 + Pos\_Article)_{j,m}$	1,332,827	0	0	0	0.693	1.946	2.773	9.686	1.054	1.201
KOL_j	1,332,827	0	0	0	0	0	1	1	0.148	0.355
Panel C: Testing sample for Hypothesis 3										
$CAR_{i,q[-3,5]}$	18,286	-1.066	-0.090	-0.040	0.004	0.048	0.099	0.867	0.005	0.090
$CAR_{i,q[-3,7]}$	18,286	-1.029	-0.096	-0.041	0.005	0.053	0.109	1.043	0.007	0.096
$RET_{i,q}$	18,285	-0.588	-0.200	-0.120	-0.033	0.063	0.185	3.646	-0.011	0.191
$RET\_Mkt\_Adj_{i,q}$	18,285	-0.594	-0.171	-0.097	-0.021	0.070	0.184	3.681	0.002	0.182

$UE_{i,q}$	18,074	-2.018	-0.0380	-0.012	0	0.008	0.025	2.344	-0.003	0.071
$Earn_{i,q}$	18,267	-0.438	-0.008	0.002	0.010	0.022	0.039	1.689	0.012	0.029
$Roa_{i,q}$	18,286	-2.623	-0.014	0.004	0.017	0.039	0.069	6.365	0.021	0.072
$BM_{i,q}$	18,286	0.039	0.314	0.470	0.672	0.873	1.036	1.652	0.675	0.271
$Size_{i,q}$	18,286	18.02	21.14	21.74	22.51	23.46	24.45	28.66	22.67	1.356
$Loss_{i,q}$	18,286	0	0	0	0	0	1	1	0.179	0.383

Table 5

Validating the misinformation regulation shock

This table validates the effects of misinformation regulation on account deletions. We report the impact of misinformation regulation on the number of identified deleted finfluencers and active regular users by months (from January 2022 to the end of November 2023). $Post_m$ indicates whether the misinformation regulation has been enforced in month m. IP_m is an indicator variable, equal to 1 since August 2022, to control the impact of mandatory IP disclosure policy on account deletion. All specifications are estimated using OLS, and time-series heteroscedasticity-consistent standard errors are used. We report t-statistics are shown in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	(1)	(2)	(3)
Dep. Variable	# deleted KOLs	# deleted active regular users	(# deleted KOLs - # deleted active regular users)
$Post_m$	16.714***	2.444	14.270***
	(3.79)	(1.03)	(3.41)
IP_m	7.571**	3.000	4.571
	(2.59)	(1.44)	(1.26)
Constant	3.714***	9.000***	-5.286**
	(3.77)	(6.19)	(-2.70)
R-squared	0.676	0.217	0.580
No. of observations	23	23	23

Table 6

The relationship between the likelihood of finfluencers' deletion and their posting behavior

This table reports the relationship between the likelihood of finfluencers being targeted for deletion and their posting behavior. Our interest is the difference in this relationship pre- and post-regulation. $Del\_KOL_{j,pre}$ ($Del\_KOL_{j,post}$) indicates whether finfluencer j was deleted between March 1, 2022 (March 1, 2023) to the end of November 2022 (November 2023). $Avg\_Rsent_{j,pre}$ ($Avg\_Rsent_{j,post}$) is calculated by averaging the sentiment scores of all finfluencer j's posts in January and February 2022 (January and February 2023), and we assign relatively neutral (0) if user j do not post during pre-regulation (post-regulation) period. Model specifications are estimated using Logistic model and rare event logistics model (Penalized Maximum Likelihood Estimation). We report z-statistics in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	Logistic model		Logistic model in rare event	
	Pre-regulation	Post-regulation	Pre-regulation	Post-regulation
	(1)	(2)	(3)	(4)
Dep. Variable	$Del\_KOL_{j,pre}$	$Del\_KOL_{j,post}$	$Del\_KOL_{j,pre}$	$Del\_KOL_{j,post}$
Avg_Rsent_j	-2.044**	-3.063***	-2.025**	-3.052***
	(-2.06)	(-6.60)	(-2.05)	(-6.58)
$Star\_KOL_j$	-1.249***	-1.260***	-1.225***	-1.257***
	(-3.57)	(-8.08)	(-3.53)	(-8.07)
Constant	-4.128***	-2.226***	-4.111***	-2.224***
	(-11.46)	(-14.47)	(-11.47)	(-14.47)
Diff. in Coef. of Avg_Rsent_j	-1.019**		-1.028*	
Pseudo R-squared	0.024	0.035	NA	NA
# Deleted KOLs	47	252	47	252
# Non-deleted KOLs	8,888	8,581	8,888	8,581
No. of observations	8,935	8,833	8,935	8,833

Table 7

The effects of misinformation regulation on the non-deleted finfluencers' posting behavior

This table reports diff-in-diffs estimates of the effects of misinformation regulation on the non-deleted finfluencers' posting behavior. Relative sentiment ($RSent_{j,m}$) is user j's monthly relative sentiment by averaging the sentiment scores of their posts. $Ln(1+Neg\_Article)_{j,m}$ is the natural log of one plus number of posts with sentiment score below 0 made by user j in month m. $Ln(1+Pos\_Article)_{i.m}$ is the natural log of one plus number of posts with sentiment score above 0 made by user j in month m. $Ln(1+Articles)_{i.m}$ is the natural log of one plus the number of user j's posts in month m. KOL_i is an indicator variable, equal to 1 if user j is non-deleted finfluencer (treated group), and 0 for non-deleted active regular users (control group). All specifications are estimated using OLS and include fixed effects for individual users, calendar year-month. Heteroscedasticity-consistent standard errors are clustered at users' IP address (province) level, and t-statistics are shown in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	(1)	(2)	(3)	(4)
Dep. Variable	$RSent_{j,m}$	$Ln(1+Neg\_Article)_{j,m}$	$Ln(1+Pos\_Article)_{j,m}$	$Ln(1+Articles)_{j,m}$
$KOL_j * Post_m$	0.015***	-0.011***	-0.076***	-0.070***
	(12.96)	(-3.55)	(-9.64)	(-8.62)
Calendar year-month FE	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
R-squared	0.318	0.316	0.429	0.429
# Unique non-deleted KOLs	8,581	8,581	8,581	8,581
# Unique non-deleted active regular users	49,368	49,368	49,368	49,368
No. of observations	1,332,827	1,332,827	1,332,827	1,332,827

Table 8

The effects of misinformation regulation on earnings response coefficients (ERC)

This table reports diff-in-diffs estimates of the effects of misinformation regulation on earnings response coefficients (ERC). $CAR_{i,q[-3,n]}$ is the cumulative abnormal returns for firm i during the period from three-trading-days before to n-trading-days after the release date of earnings news for fiscal quarter q, where the window starts three-trading-days before the release date to circumvent the information leakage. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards (cut-off value is 43) in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Control variables include interacted ROA, firm size, book-to-market value, and an indicator variable for loss with current unexpected earnings. The fiscal year-level control variables ($Size_{i,2022}$, $BM_{i,2022}$, and $Roa_{i,2022}$) used in PSM model (4) are also included. All specifications are estimated using OLS and include controls and fixed effects for fiscal quarter, calendar year-month, and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level, and t-statistics are shown in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	(1)	(2)
Dep. Variable	$CAR_{[-3,5]}$	$CAR_{[-3,7]}$
$Treat_i * Post_{fqtr,q} * UE_{i,q}$	0.145***	0.150***
	(2.74)	(2.66)
Controls	Yes	Yes
Fiscal quarter FE	Yes	Yes
Calendar year-month FE	Yes	Yes
Industry FE	Yes	Yes
R-squared	0.034	0.034
# firms	2,378	2,378
No. of observations	18,074	18,074

Table 9

The effects of misinformation regulation on future earnings response coefficients (FERC)

This table reports diff-in-diffs estimates of the effects of misinformation regulation on future earnings response coefficients (FERC). $RET_{i,q}$ is the realized buy-and-hold returns over the entire fiscal quarter q for firm i, calculated from the end of fiscal quarter $q-1$ to the end of fiscal quarter q. $RET\_Mkt\_Adj_{i,q}$ is market-adjusted realized buy-and-hold returns, where the realized market returns are equal-weighted. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards (cut-off value is 43) in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Control variables include interacted ROA, firm size, book-to-market value, and an indicator variable for loss with future earnings. The fiscal year-level control variables ($Size_{i,2022}$, $BM_{i,2022}$, and $Roa_{i,2022}$) used in PSM model (4) are also included. All specifications are estimated using OLS and include controls and fixed effects for fiscal quarter, calendar year-month, and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level, and t-statistics are shown in parentheses. * *p*<0.1; ** *p*<0.05; *** *p*<0.01.

	(1)	(2)
Dep. Variable	RET	RET_Mkt_Adj
$Treat_i * Post_{fqtr,q} * Earn_{i,q+1}$	-0.555**	-0.560**
	(-2.41)	(-2.41)
Controls	Yes	Yes
Fiscal quarter FE	Yes	Yes
Calendar year-month FE	Yes	Yes
Industry FE	Yes	Yes
R-squared	0.123	0.025
# firms	2,378	2,378
No. of observations	15,859	15,859

Table 10

The sensitivity of ERC (FERC) to the negative contemporaneous (future) earnings surprise

This table reports the sensitivity of ERC (FERC) to the negative contemporaneous (future) earnings surprise. For columns (1) and (2), we estimate the model specification (8) in Appendix C for the sensitivity of ERC to the negative contemporaneous earnings surprise. For columns (3) and (4), we estimate the model specification (10) in Appendix C for the sensitivity of FERC to the negative future earnings surprise. All specifications are estimated using OLS and include controls and fixed effects for fiscal quarter, calendar year-month, and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level, and t-statistics are shown in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	ERC		FERC	
	(1)	(2)	(3)	(4)
Dep. Variable	$CAR_{[-3,5]}$	$CAR_{[-3,7]}$	RET	RET_Mkt_Adj
$Treat_i * Post_{fqtr,q} * UE_{i,q}$	-0.039	-0.007		
	(-0.52)	(-0.09)		
$* Neg\_surprise_{i,q}$	0.333***	0.296**		
	(2.82)	(2.31)		
$Treat_i * Post_{fqtr,q} * Earn_{i,q+1}$			-1.226***	-1.231***
			(-2.94)	(-2.93)
$* Neg\_surprise_{i,q+1}$			0.651	0.651
			(1.31)	(1.30)
Controls	Yes	Yes	Yes	Yes
Fiscal quarter FE	Yes	Yes	Yes	Yes
Calendar year-month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R-squared	0.037	0.036	0.138	0.040
No. of observations	18,074	18,074	15,859	15,859

Online Appendix

Figure OA-1

The confusion matrix of online information

This figure illustrates the confusion matrix to identify various types of finfluencers' post information. When finfluencers' ex-ante posts align with the ex-post earnings announcements (either positive or negative), it indicates that finfluencers are disseminating accurate information, thereby helping to uncover fundamental information. Conversely, if finfluencers' ex-ante posts are positive but the earnings announcement reveals negative information, it suggests that finfluencers are spreading positive misinformation. Similarly, if finfluencers' ex-ante posts are negative while the earnings announcement is positive, it indicates that finfluencers are disseminating negative misinformation. It is worth noting that this is merely a stylized framework to illustrate the core concept of misinformation. However, the dynamics of the real online world are far more complex. Misinformation can still arise even when there is alignment between finfluencers' ex-ante posts and future EA. For instance, finfluencers may overshoot anticipated positive or negative news ex-ante.

	Earnings Announcement's Disclosure	
KOLs' Posts	Positive	Negative
Positive	Valid information	Positive misinformation
Negative	Negative misinformation	Valid information

Figure OA-2

The number of deleted finfluencers and regular users

This figure shows the continuous upward trend in finfluencers' account deletion, alongside the regular users' account deletion pattern, following a random walk pattern. The red line is the number of deleted finfluencers in corresponding months, and the blue dashed line is the number of deleted regular users. Furthermore, we use annotations for significant events during this period, which are the enforcement of IP disclosure in August 2022 and Qinglang Operation in March 2023, respectively.

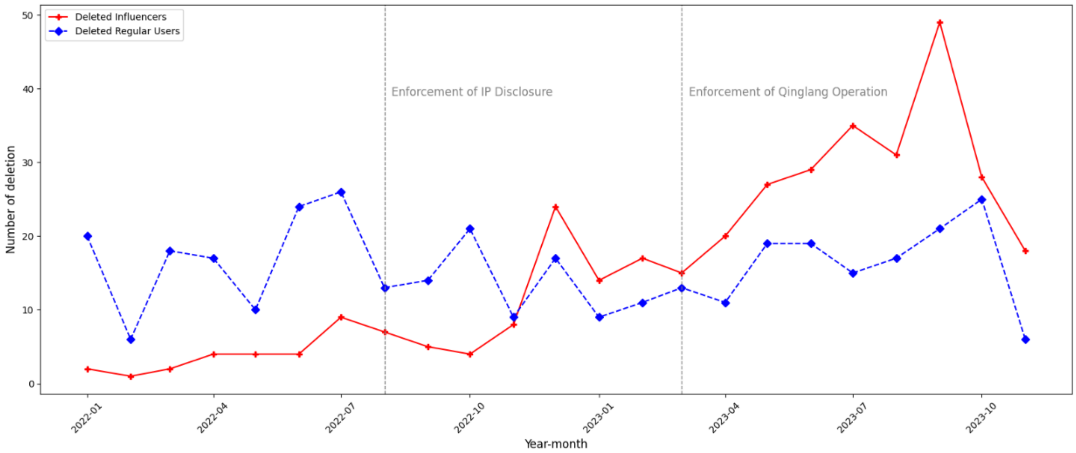


Figure OA-3

Test for parallel trends assumption

This figure shows the test for parallel trends assumption for the ERC and FERC models. The reported coefficients represent the differences in ERC (or FERC) between treated and control firms at each event time relative to the treatment. We define relative time based on the fiscal quarter in which misinformation regulation was first implemented: the value of 0 represents 1st fiscal quarter of 2023, when the Qinglang Operation was first enacted. -4 denotes the earliest period in our sample, corresponding to the annual report of 2021, which was disclosed in 2022 (notably, we remove the straddled observations of 2022 4th fiscal quarter), while 4 represents the final period in our sample, the 1st fiscal quarter of 2024. For the ERC model, we have five observed five fiscal quarters post-regulation (from Q1 2023 to Q1 2024). However, we have only four observed quarters post-regulation for the FERC model, as future earnings data for Q1 2024 was unavailable at the time of data collection. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards (cut-off value is 43) in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Control variables include interacted ROA, firm size, book-to-market value, and an indicator variable for loss with current unexpected earnings. The fiscal year-level control variables ($Size_{i.2022}$, $BM_{i.2022}$, and $Roa_{i.2022}$) used in PSM model (4) are also included. All specifications are estimated using OLS and include controls and fixed effects for fiscal quarter, calendar year-month, and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level. The vertical bars represent 99% confidence intervals.

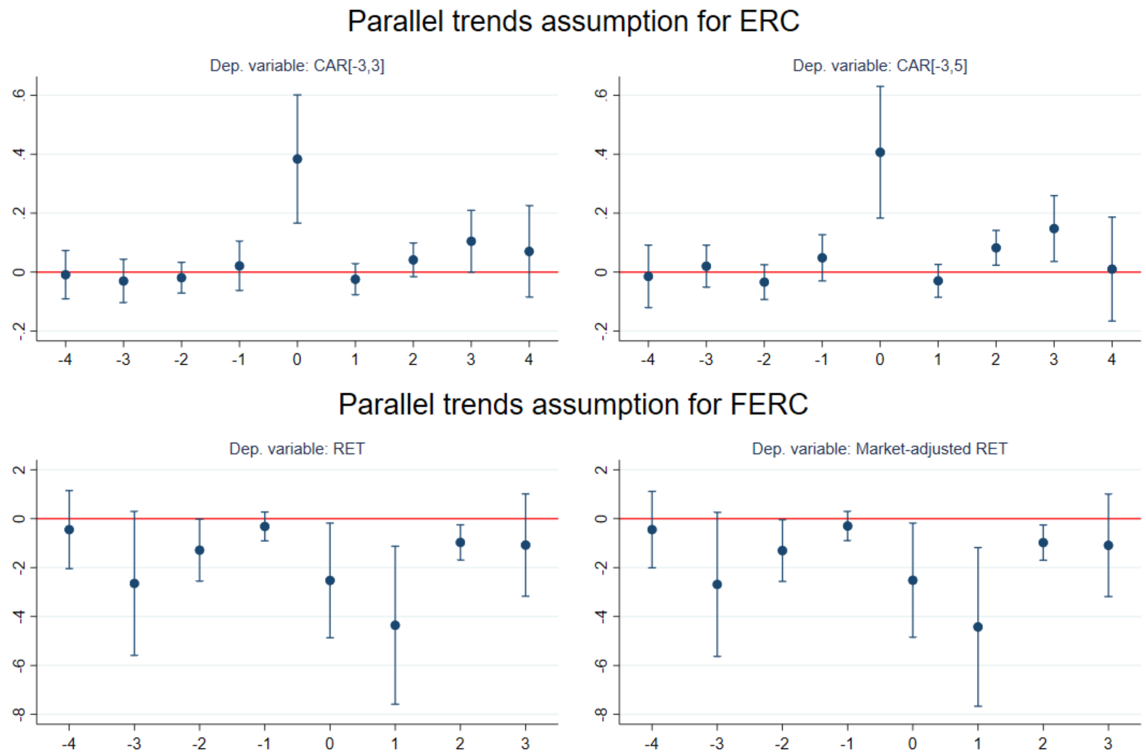


Figure OA-4

The average number of firms' affiliated deleted finfluencers

This figure reports the average number of firms' affiliated deleted finfluencers over time. We use the observed heterogeneous treatment effect for treated and control firms post-regulation to verify whether the treatment assignment based on the likelihood of being affected by Qinglang Operation in pre-regulation period is valid. Each firm's affiliated deleted finfluencers are those at least posted once in relevant firm's stock message board since January 1, 2022. The red line indicates the trend of treated firms, and the blue line represents control firms. The black dashed line indicates the difference between treated and control firms. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Furthermore, we use annotations for significant events during this period, which are the enforcement of IP disclosure in August 2022 and Qinglang Operation in March 2023, respectively.

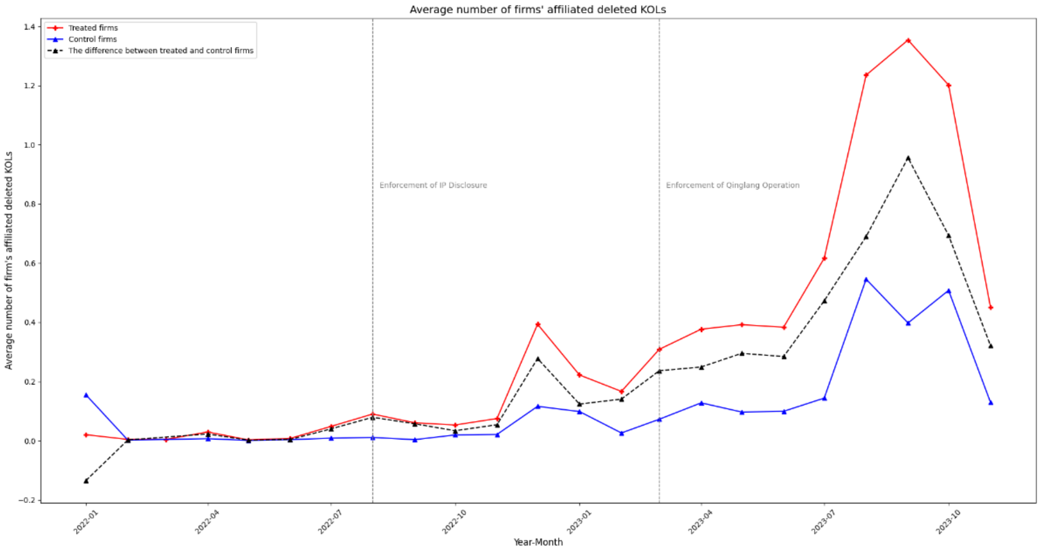


Figure OA-5

Placebo test: permutation test for estimates (randomly assigned treatment status)

This figure shows Fisher's permutation test (also known as the re-randomization test) using randomly assigned treatment status. Given the randomly assigned treatment status, the re-randomization process tests the distribution of the ERC and FERC estimates based on mode specifications (5) and (6), respectively. The bars illustrate the histogram of 2,000 estimates from placebo tests. We randomly reassign the pseudo-treatment status to all firms while maintaining the real-treated timing. The black line is the estimated normal distribution.

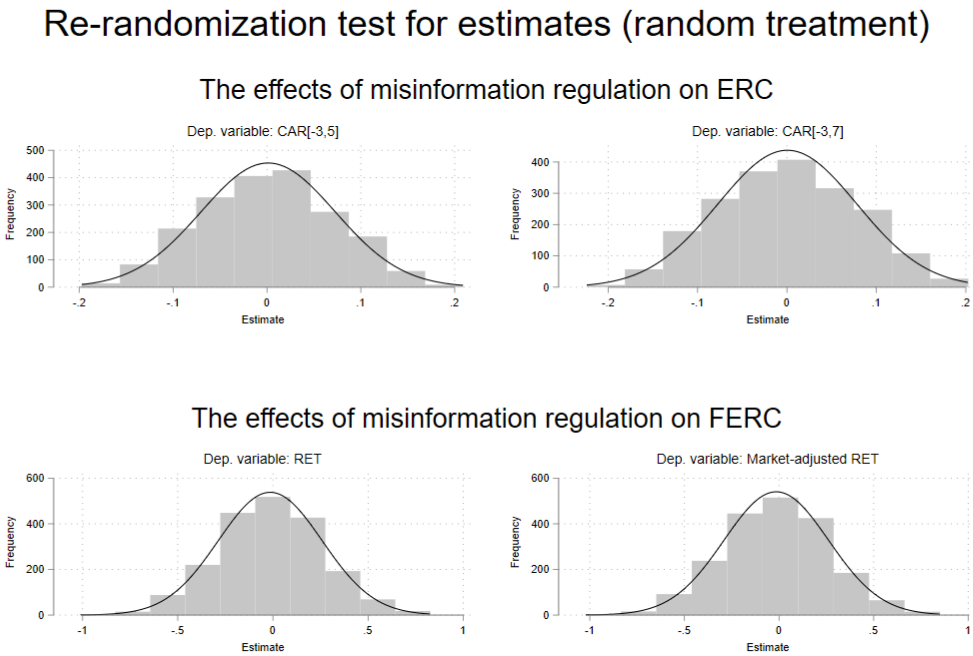


Figure OA-6

Placebo test: permutation test for t-values (randomly assigned treatment status)

This figure shows Fisher's permutation test (also known as the re-randomization test) using randomly assigned treatment status. Given the randomly assigned treatment status, the re-randomization process tests the distribution of t-values of the ERC and FERC estimates based on mode specifications (5) and (6), respectively. The bars illustrate the histogram of 2,000 estimates from placebo sample. We randomly reassign the pseudo-treatment status to all firms while maintaining the real-treated timing. The black line is the estimated normal distribution.

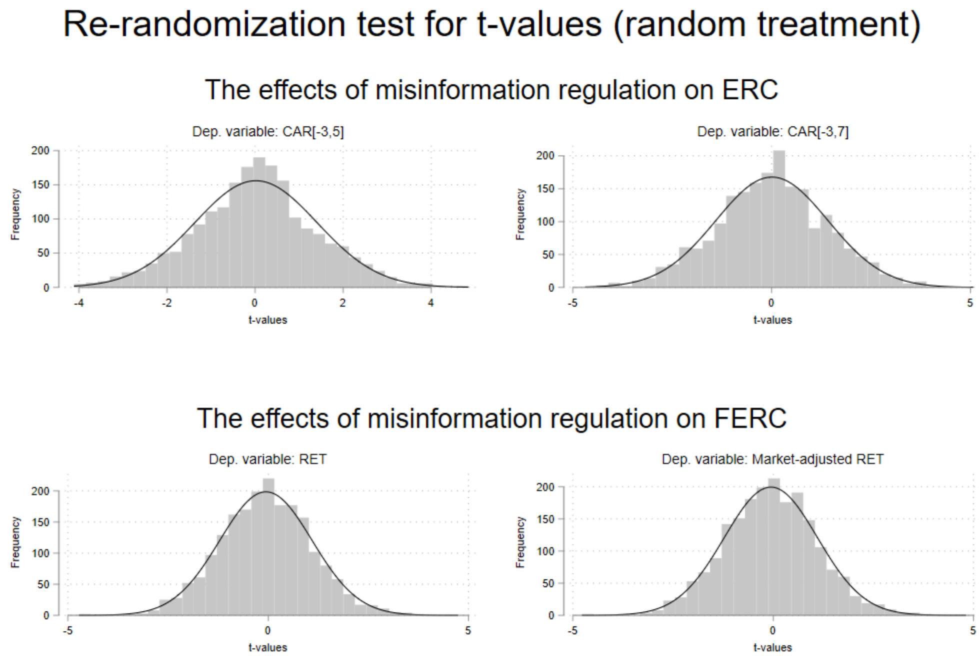


Figure OA-7

Placebo test: permutation test for estimates (randomly assigned treated timing)

This figure shows Fisher's permutation test (also known as the re-randomization test) using randomly assigned treated timing. Given the randomly assigned treated timing, the re-randomization process tests the distribution of the ERC and FERC estimates based on mode specifications (5) and (6), respectively. The bars illustrate the histogram of 2,000 estimates from placebo tests. We randomly reassign the pseudo-treated timing while maintaining the real treatment assignment. The black line is the estimated normal distribution.

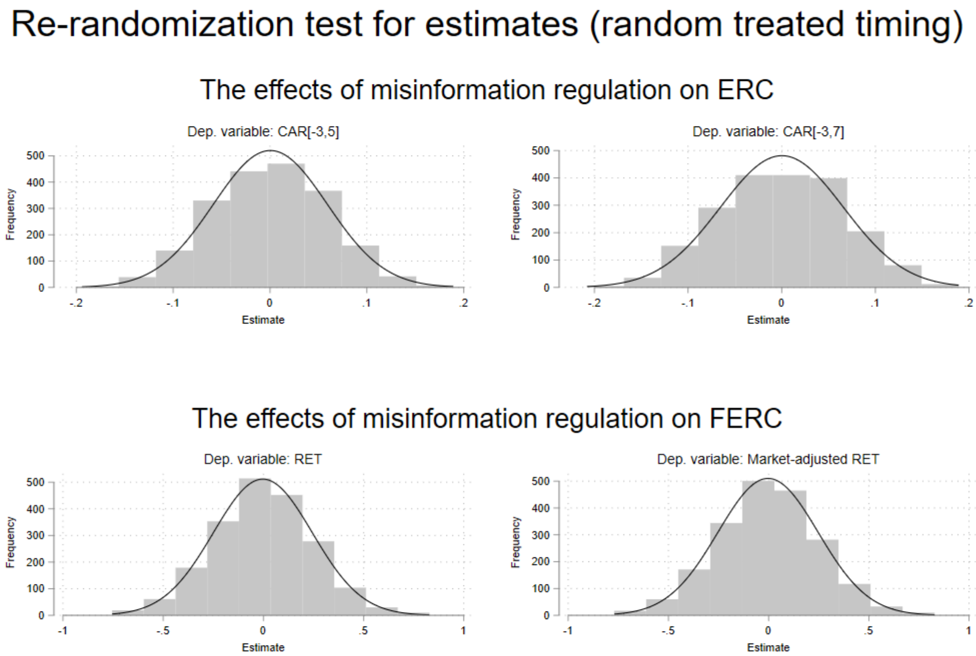


Figure OA-8

Placebo test: permutation test for t-values (randomly assigned treated timing)

This figure presents Fisher's permutation test (also known as the re-randomization test) using randomly assigned treated timing. Given the randomly assigned treated timing, the re-randomization process tests the distribution of t-values of the ERC and FERC estimates based on mode specifications (5) and (6), respectively. The bars illustrate the histogram of 2,000 estimates from placebo sample. We randomly reassign the pseudo-treated timing while maintaining the real treatment assignment. The black line is the estimated normal distribution.

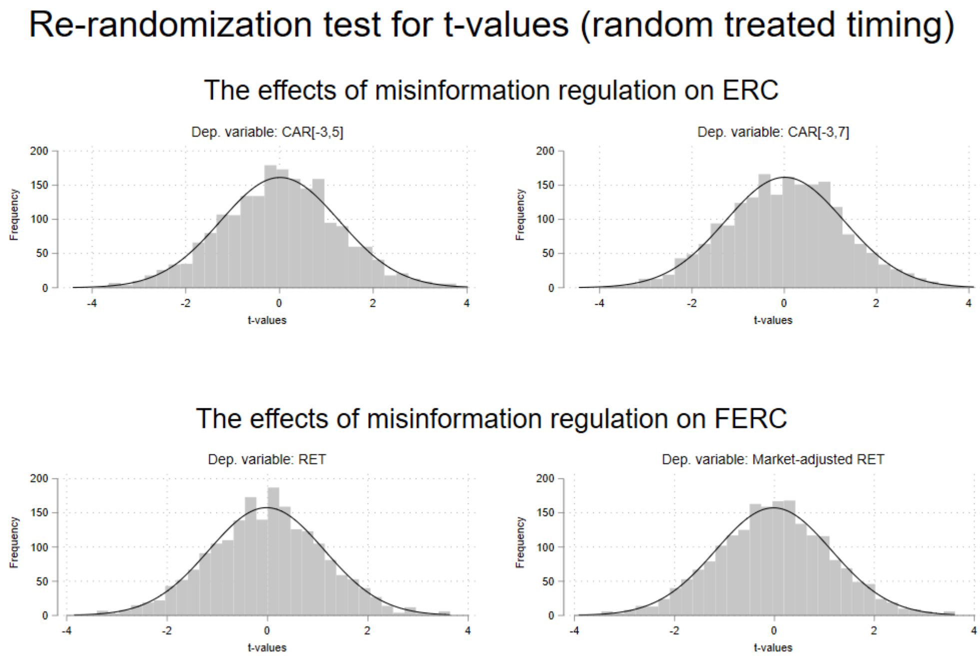


Table OA-1

Post-level summary statistics

This table reports the post-level descriptive statistics, including Read, Comment, Title Length and Sentiment, in which each observation is a unique post by identified finfluencers and active regular users. Read measures the readership, which represents the total historical number of individuals who have clicked and read the post. Comment measures the total number of responses that the post receives. Title Length is the number of the Chinese characters in the post's title. Sentiment is the sentiment score of post's title, measured by fine-tuning FinBERT, ranging from -0.5 to 0.5 where -0.5 (0.5) represents the most negative (positive) sentiment. We also report the difference in mean for each variable pre- and post-regulation. *t* -statistics are reported; * p<0.1; ** p<0.05; *** p<0.01.

	Pre-regulation						Post-regulation						Post - Pre	
	# obs.	P25	P50	Mean	P75	SD	# obs.	P25	P50	Mean	P75	SD	Diff	*t*-stat
Read	7,050,643	169	269	835.1	491	5241	3,431,101	95	175	436.8	324	1569	-398.237	-137.776***
Comment	7,050,643	0	0	4.572	2	41.41	3,431,101	0	0	2.909	2	14.82	-1.663	-72.179***
Title Length	7,050,643	11	20	18.76	25	8.829	3,431,101	9	17	16.80	25	8.391	-1.959	-342.513***
Sentiment	7,050,643	0.283	0.486	0.369	0.498	0.193	3,431,101	0.222	0.475	0.350	0.498	0.203	-0.019	-150.087***

Table OA-2

User-level descriptive statistics

This table reports the user-level descriptive statistics for deleted and non-deleted finfluencers, as well as active regular users, respectively. For each type of users, we show the basic user profile information: their influence level (Star), user age (Age), the number of followers (Follower), the number of other users the user follows (Following), total historical visits to the user profile page (Visit), the number of posts the user published (Articles), the number of reply the user comments (Reply), the number of stock the user follows (Stock). For variable definitions, please refer to Appendix D.

Variable	# obs. (unique user)	p5	p25	p50	Mean	p75	p95	SD
Panel A: Deleted finfluencers								
Star	357	0	2.500	3	2.665	3.500	4	1.293
Age	357	2.300	3.500	5.800	6.285	8.600	11.60	3.180
Following	357	0	1	5	21.20	22	99	44.74
Follower	357	0	0	0	746.9	0	3413	3848
Visit	357	11020	15520	28221	124946	66725	518002	388212
Articles	357	221	646	1181	1898	2135	5185	3149
Reply	357	365	1143	2111	4038	4571	12764	6206
Stock	357	0	5	18	68.98	68	400	118.6
Panel B: Non-deleted finfluencers								
Star	8,581	3	3.500	3.500	3.683	4	4.500	0.514
Age	8,581	2.500	4.300	7.700	7.553	10	14.20	3.621
Following	8,581	0	2	12	47.61	52	193	108.9
Follower	8,581	570	1032	1375	4790	2984	20689	13178
Visit	8,581	15622	39906	85553	405469	255049	1553430	1647856
Articles	8,581	267	694	1299	2573	2867	8579	4056
Reply	8,581	35	1110	3108	6229	7164	22315	10462
Stock	8,581	0	8	34	101.5	126	480	142.5
Panel C: Deleted active regular users								

Star	277	0	1.500	2	1.717	2	2	0.659
Age	277	2	2.300	2.800	2.897	3.400	4.500	0.796
Following	277	0	0	1	6.740	6	28	15.36
Follower	277	0	0	0	2.480	2	10	9.372
Visit	277	536	1187	1538	1525	1958	2331	545.7
Articles	277	114	152	180	209.9	239	387	106.6
Reply	277	14	89	178	246.6	321	753	243.2
Stock	277	0	5	16	50.49	50	226	89.88
Panel D: Non-deleted active regular users								
Star	49,368	1.500	2	2	1.995	2	2.500	0.302
Age	49,368	2	2.500	2.900	3.160	3.700	4.800	0.976
Following	49,368	0	1	3	11.92	10	45	38.02
Follower	49,368	0	1	3	4.913	5	15	11.03
Visit	49,368	572	1056	1491	1473	1921	2298	540.1
Articles	49,368	110	151	193	224.2	260	431	137.2
Reply	49,368	11	73	157	218.0	291	623	236.7
Stock	49,368	1	12	43	96.97	122	440	128.6

Table OA-3

Firm-level descriptive statistics

This table reports the summary statistics of firm-level variables for matched firms. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards (cut-off value is 43) in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Control variables include interacted ROA, firm size, book-to-market value, and an indicator variable for loss with future earnings. For variable definitions and construction, see Appendix D. * p<0.1; ** p<0.05; *** p<0.01.

	Pre-regulation								Post-regulation							
	Treated firms			Control firms			Treated - Controls		Treated firms			Control firms			Treated - Controls	
	# obs.	Mean	SD	# obs.	Mean	SD	Diff	t-stat	# obs.	Mean	SD	# obs.	Mean	SD	Diff	t-stat
Matching variables:																
Size	1,189	22.57	1.363	1,189	22.63	1.323	-0.064	-1.165	1,189	22.64	1.378	1,189	22.72	1.328	-0.075	-1.344
Roa	1,189	0.026	0.078	1,189	0.027	0.042	-0.001	-0.251	1,189	0.015	0.040	1,189	0.018	0.045	-0.003	-1.793
BM	1,189	0.650	0.260	1,189	0.674	0.267	-0.023	-2.173	1,189	0.654	0.266	1,189	0.701	0.264	-0.047	-4.314
Cumulative abnormal returns (%):																
$CAR_{[-3,5]}$	1,189	0.246	5.819	1,189	-0.130	4.727	0.376	1.731	1,189	0.699	4.610	1,189	1.249	4.143	-0.551	-3.063
$CAR_{[-3,7]}$	1,189	0.508	6.132	1,189	0.189	5.024	0.319	1.389	1,189	0.776	4.960	1,189	1.349	4.414	-0.573	-2.976
Buy-and-hold returns (%):																
RET	1,188	0.150	11.24	1,189	-1.689	8.637	1.839	4.472	1,189	-1.048	9.712	1,189	-1.874	6.864	0.826	2.394
RET_Mkt_Adj	1,188	1.055	11.20	1,189	-0.606	8.566	1.661	4.059	1,189	0.633	9.671	1,189	-0.278	6.869	0.911	2.647
Other variables:																
UE	1,174	0.002	0.063	1,174	-0.006	0.042	0.008	3.594	1,189	-0.007	0.050	1,189	-0.003	0.036	-0.003	-1.935
$Earn$	1,189	0.013	0.030	1,189	0.015	0.022	-0.002	-2.263	1,189	0.008	0.020	1,189	0.011	0.021	-0.003	-3.704
$Loss$	1,189	0.166	0.372	1,189	0.121	0.326	0.045	3.106	1,189	0.209	0.407	1,189	0.179	0.384	0.030	1.866

Table OA-4

Test for parallel trends assumption based on pre-treatment sample

This table validates the parallel trends assumption of our diff-in-diffs estimates for ERC and FERC results. We re-estimate our main results using the sample of EA released within the two-year period before the enactment of the Qinglang Operation (Jan. 2021 to the end of 2022) to test the pre-trends. Using 2022 Q1 fiscal quarter, one fiscal year prior to the implementation of misinformation regulation, as the pseudo-treated timing, we re-run our estimates based on model specifications (5) for ERC and (6) for FERC, respectively. Treated (control) firms are those ranked in the top (bottom) half based on the number of finfluencers with more negative tones on their stock message boards (cut-off value is 43) in the pre-regulation period. To address the endogeneity issue, we match treated firms with control firms based on the ROA, firm size and book-to-market value, using 0.01 caliper. Control variables include interacted ROA, firm size, book-to-market value, and an indicator variable for loss with current unexpected earnings. The fiscal year-level control variables ($Size_{i,2022}$, $BM_{i,2022}$, and $Roa_{i,2022}$) used in PSM model (4) are also included. All specifications are estimated using OLS and include controls and fixed effects for fiscal quarter, calendar year-month, and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level, and t-statistics are shown in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	ERC		FERC	
	(1)	(2)	(3)	(4)
Dep. Variable	$CAR_{[-3,5]}$	$CAR_{[-3,7]}$	RET	RET_Mkt_Adj
$Treat_i * Pseudo\_Post_{fqtr,q} * UE_{i,q}$	-0.005	-0.012		
	(-0.08)	(-0.19)		
$Treat_i * Pseudo\_Post_{fqtr,q} * Earn_{i,q+1}$			-0.083	-0.065
			(-0.26)	(-0.20)
Controls	Yes	Yes	Yes	Yes
Fiscal quarter FE	Yes	Yes	Yes	Yes
Calendar year-month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R-squared	0.033	0.032	0.118	0.048
# firms	2,348	2,348	2,377	2,377
No. of observations	14,158	14,158	16,709	16,709

Table OA-5

Oster test for unobservable selection and coefficient stability

This table shows the Oster test for the omitted variable issue and coefficient stability. Estimates in Panel A are based on specification (5), and estimates in Panel B are based on specification (6). We estimate and report the $\hat{\delta}$ making estimated treatment effects invalid (i.e., $\beta = 0$) based on a bias-adjusted treatment effect bound $R_{max} = 1.3\tilde{R}$. Oster (2019) suggests that the current estimated coefficient can be considered stable, if it would be driven to 0 only when the importance of unobservable variables exceeds that of observable variables (i.e., $\hat{\delta} > 1$). Satyanath et al. (2017) demonstrate that if the value of $\hat{\delta}$ is less than 0, the bias-adjusted coefficient should be greater than the current estimate, thereby confirming the robustness of current results. All specifications are estimated OLS and include controls and fixed effects for fiscal quarter, calendar year-month and industry. Heteroscedasticity-consistent standard errors are clustered at the industry level. * p<0.1; ** p<0.05; *** p<0.01.

	Estimated causal effects ($\hat{\beta}$)	$\hat{\delta} \mid (R_{max} = 1.3\tilde{R}, \beta = 0)$	Pass Oster test?
Panel A: Estimated ERC ($\boldsymbol{Treat_i * Post_{fqtr,q} * UE_{i,t,q}}$)			
$CAR_{[-3,5]}$	0.145***	1.267	Yes
$CAR_{[-3,7]}$	0.150***	1.062	Yes
Panel B: Estimated FERC ($\boldsymbol{Treat_i * Post_{fqtr,q} * Earn_{i,t,q+1}}$)			
RET	-0.555**	4.902	Yes
RET_Mkt_Adj	-0.560**	11.387	Yes