Investor-initiated Online Communications and Corporate Misconduct

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Abstract

China's stock exchanges launched investor interaction platforms in 2010 and 2013 to empower retail investors. Investor-initiated interactive communications on these platforms are associated with a reduction of the propensity of corporate misconduct. The identified effect is associated with information asymmetry, but not with the impact of internal and external corporate governance monitoring. Our findings indicate that online investor-initiated communications enhance firm value. The investor interactive platforms serve as an important monitor of corporate misconduct, which could be adopted by other regulatory jurisdictions.

***Keywords*:** Corporate misconduct; Investor-initiated communications; Quasi-social media; Information asymmetry; Value effects

***JEL Classification*:** D83, G15, G34, G39, O30

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Abstract

China’s stock exchanges launched investor interaction platforms in 2010 and 2013 to empower retail investors. Investor-initiated interactive communications on these platforms are associated with a reduction of the propensity of corporate misconduct. The identified effect is associated with information asymmetry, but not with the impact of internal and external corporate governance monitoring. Our findings indicate that online investor-initiated communications enhance firm value. The investor interactive platforms serve as an important monitor of corporate conduct, which could be adopted by other regulatory jurisdictions.

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Investor-initiated Communications and Corporate Misconduct

1. Introduction

The advent of various social media platforms has shaped the way information is disseminated. Relying on internet-based technologies, social media generates insights by facilitating the exchange of ideas, opinions, and factual information (e.g., Cao, Fang, and Lei, 2021; Ang, Hsu, Tang, and Wu, 2021; Chen, De, Hu, and Hwang, 2014). Investors can easily acquire information about capital markets and immediately post their opinions about stocks to a broad audience (Bartov, Faurel, and Mohanram, 2018). A growing body of literature examines the impact of various social media on firm behavior and capital markets (e.g., Lee, Hutton, and Shu, 2015; Feng and Johansson, 2019; Cookson and Niessner, 2020; Gómez-Carrasco, Guillamón-Saorín, and Garcia Osma, 2021; Bilinski, 2022; Guo, Yu, and Faff, 2022; Lee, Lee, and Zhong, 2022). In this paper, we examine the relation between micro (totally firm-specific) data on social media posts and corporate misconduct.

Based on the theoretical crime model of Becker (1968), media ex-ante can reduce corporate misconduct if the expected benefits of committing misconduct become less than the expected costs. The expected costs are expected to be higher if social media diffuses news faster than other communication media and to a larger audience that makes investors more aware of the firms and its activities (Merton, 1987). If social media activity leads to greater attention, awareness and action by non-insiders, then social media activity is expected to be causally related to corporate misconduct. However, if the awareness and/or learning of market participants (investors and regulators) do not increase materially from interactive-platform communications due to the neglect of market participants or due to firm responses that lack specificity or truthfulness, then no relation between interactive-platform communications and corporate misconduct may exist. Thus, whether investor-initiated online communications affect the incidence of corporate misconduct is an empirical question.

We address this research question by examining the relation between corporate misconduct and retail investor activity on China's online interactive platforms.[1] In 2010 and 2013, the Shenzhen and Shanghai Stock Exchanges launched the investor interactive platforms, *Easy Interaction* and *E-interaction*, respectively. These quasi-social media platforms allow investors to directly ask questions to firms. Since firm responses are quasi-mandatory, this provides us with a unique setting for directly investigating the monitoring role of this social medium on corporate misconduct.

Our baseline regression results show a negative relation between investor-initiated communications and the incidence of corporate misconduct, indicating that China's investor interactive platforms as a quasi-social media play an important role in monitoring corporate misconduct. For example, one-standard-deviation increases in the logarithm of the number of questions asked by investors and replies made by firms are associated with 6.2% and 7.7% decreases in the probability of corporate misconduct.[2] The results are robust to alternative measures of interactions and an analysis using investor sentiment extracted from investor-initiated communications with firms.

To alleviate endogeneity concerns and address identification issues, we adopt the difference-in-differences (DiD) approach based on the staggered adoption of the online interactive platforms in China for investor-initiated communications with firms. We focus on the interactive platform launched by the Shenzhen Stock Exchanges in 2010. As the Shanghai Stock Exchange launched the interactive platform in 2013, the staggered adoption of the two interactive platforms provides us with an ideal exogenous shock for identification purposes. Our DiD results show that firms listed in the Shenzhen Stock Exchange are likely to reduce the incidence of corporate misconduct than their propensity-score-matched control firms listed in the Shanghai Stock Exchange. We find

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[1] We note that the literature uses the terms "interactive platforms" and "interaction platforms" or both interchangeably (e.g., Cheng, Chiao, and Fang et al., 2020) when examining these platforms.

[2] We use the listcoef command by Long and Freese (2014) in Stata to calculate standardized coefficients for the probit model.

that the negative relation is more pronounced for firms with high information asymmetry, and that internal or external corporate governance monitors do not negate the negative association.

Investor-initiated communications with firms not only reduce the incidence of corporate misconduct, but also increase firm value, as measured by Tobin's Q. One-standard-deviation increases in investor questions and firm responses increase firm value by 9.17% and 5.52% in the year of the interactions between investors and firms, and 3.33% and 2.36% in the year after the interactions, respectively.

Our study makes three contributions to the literature. First, we provide new insights into the effect of social and other transmission/exchange media on the incidence of corporate misconduct. Although social media reduce information asymmetry (Blankespoor, Miller, and White, 2014; Bartov, Faurel, and Mohanram, 2018; Firk, Hennig, and Wolff, 2020) and ameliorate inefficient markets, few studies investigate the impact of social media on corporate misconduct. Our research complements the contemporaneous study of Heese and Pacelli (2023), who find that social media can reduce corporate misconduct. Unlike their study that examines the link between corporate misconduct in the U.S. and aggregated Twitter volume, we examine the direct (and not indirect) link between corporate misconduct and the questions and replies posted on two quasi-social media platforms. Our study is most closely related to the concurrent work by Li, Wang, and Zhang (2023b), who find that the launch of an investor-initiated platform by the Shenzhen Stock Exchange deters real earnings management. Another paper close to ours is the ex-post study by Zhou, Ye, and Lan et al. (2021), who find that attention arising from social media on corporate violations in China helps firms to take corrective actions and redress violations. In contrast to their paper, we find that investor-initiated communications with firms on the interactive platforms can serve as "watchdogs" to reduce the likelihood of the incidence of corporate misconduct.

Second, our study contributes to the growing literature on the role of China's online interactive platforms. Extant research finds that online interactive platforms deter earnings management (Li, Wang, and Zhang, 2023b), curb stock price crash risk (Ding, Lyu, and Chen, 2018; Li and Lu, 2022; Li, Wang, and Zhang, 2023a), reduce the profitability of insider trades (Xie, Xu, Jiang, and Fu, 2023), and affect a stock's idiosyncratic risk (Xu, Zheng, and Luo, 2022). Extant research also finds that online interactive platforms enhance firm cumulative abnormal returns (Ding, Lyu, and Huang, 2018), increase investors' perceptions of earnings information (Huang and Ying, 2022), and increase firm trading volume and return volatility, and improve market liquidity and price informativeness (Lee and Zhong, 2022). Few papers examine the impact of the online interactive platforms on corporate governance. Liu (2022) finds that investor protection attributable to the *E-interaction platform* launched by the Shanghai Stock Exchange leads to lower audit fees. In a similar vein, our study focuses on the monitoring role of the interactive platforms on corporate misconduct. Our study may help improve the procedures and technologies currently used by various international regulatory authorities for financial market surveillance to prevent corporate misconduct practices.

Third, our study provides further evidence on the growing influence of retail investors in equity markets. Retail investors are usually portrayed as being unsophisticated and playing a passive role in capital markets because they have negligible power and obtain little information compared to institutional investors (Malmendier and Shanthikumar, 2007; Ang, Hsu, Tang, and Wu, 2021). The growth in social media platforms encourages and facilitates the participation of retail investors in financial markets (e.g., GameStop). Regulators and financial institutions have recognized the strength and rising influence of retail investors in capital markets (Aramonte and Avalos, 2021; Schulp, 2021). With the rising influence of retail investors, our finding that retail investors play a facilitating role in monitoring the incidence of corporate misconduct should be of value to all market participants, including regulatory authorities and policymakers.

The paper proceeds as follows. Section 2 introduces the institutional background. Section 3 reviews the literature and provides the motivation for the effect of social media on corporate misconduct in terms of China's investor-initiated interactive platforms. Section 4 describes the data and summary statistics. Section 5 reports the results of the empirical tests. Section 6 provides additional tests. Section 7 examines the effect of various potential mediating effects on our baseline results. Section 8 examines the effect of investor communications on firm value. Section 9 concludes.

2. Institutional Background

Retail investors have long dominated China's capital market trading. From 2002 to 2009, the total number of trading accounts opened by retail investors was more than 200 times the number of accounts opened by institutional investors on the Shenzhen Stock Exchange.[3] Retail investors' trading volume accounts for 89.1% of the total trading volume in the Shanghai Stock Exchange between 2013-15 according to the Shanghai Stock Exchange trading records (Titman, Wei, and Zhao, 2022).[4]

To help protect the interests of Chinese small investors, the Shenzhen and Shanghai Stock Exchanges launched two online investor interactive platforms, *Easy Interaction* and *E-Interaction*, on January 1, 2010 and July 5, 2013, respectively. Through the interactive platforms, investors can directly initiate communications with listed firms, but firms themselves do not post any questions. Companies deal with these inquiries and complaints from investors without disclosing any information not previously disclosed. These interactive platforms empower retail investors to centralize their inquiries to publicly listed firms in a timely manner while expecting a timely response from the inquired firms.[5]

These interactive platforms have a digital identity certification system to ensure that all the answers are provided exclusively by the inquired firms. Firms take legal responsibility for the

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[3] The number of trading accounts for retail and institutional investors is collected from Shenzhen Stock Exchange Fact Book. http://docs.static.szse.cn/www/market/periodical/year/W020221226388102221272.pdf

[4] The website in Chinese is available at: http://www.sse.com.cn/aboutus/research/special/c/4498328.pdf

[5] We argue that retail investors are highly likely to ask questions on the interactive platforms because they consume news and commentary that is freely available on the web, and that they are less likely to subscribe to expensive newswire services or professional advisory services. In contrast, institutional investors are less likely to consume information posted by non-professionals (Drake, Thornock, and Twedt, 2017).

accuracy of their replies. The board secretaries of participating firms must be appointed to monitor replies on behalf of the firms. The information provided by inquired firms, which is generally accurate, makes the investor interaction platforms different from the other common social media platforms such as chat rooms and investor discussion boards, where investors trust in the information delivered is low.

Firm participation in the investor interactive platforms is described as quasi-mandatory (Lee and Zhong, 2022). The two exchanges do not dictate that firms must answer investors' questions, but they assess firm participation based on the number and frequency of responses made by firms. In addition to moral suasion to encourage firms to respond, the exchanges grant "honors and awards" to firms with the best performance based on various investor-friendliness metrics.[6]

Overall, investor interactive platforms are a novel vehicle for innovative corporate communications. First, the interactive platforms are investor initiated, as investors dictate questions they are interested in or concerned about (Lee and Zhong, 2022). The investor-initiated communications are distinct from firm-dictated forms of corporate disclosure such as financial reports or corporate tweets (Lee and Zhong, 2022). For this reason, we believe that investor-initiated interactions can provide unique insights into the monitoring role that retail investors can play in deterring corporate misconduct. Second, firm participation in the investor interactive platforms is quasi-mandatory and reactive. This feature lessens the possibility that firms are less likely to engage in interactions or hide bad news from investors who ask for information clarification.

[6] Relevant information in Chinese is available at:
http://www.sse.com.cn/lawandrules/sserules/listing/stock/c/c_20150912_3985864.shtml
http://www.szse.cn/disclosure/notice/t20091225_500324.html

3. Prior Literature and Motivation for the Relation

3.1 The traditional media as a monitor of corporate misconduct

Investors have long relied on traditional media to acquire timely and relevant information about firms (Bartov, Faurel, and Mohanram, 2018). The press affects firms and financial markets, as it gradually diffuses public information to investors (Peress, 2004). Dyck, Morse, and Zingales (2010) argue that the media works as an effective external governance mechanism for misconduct detection in U.S. corporations. When internal corporate governance fails to detect misconduct, the media works as an effective external mechanism that helps detect 13% of corporate misconduct, or 24% of misconduct cases that are value-weighted by the sum of fines and settlements associated with the improprieties (Dyck, Morse, and Zingales, 2010).

As a traditional information channel, the press can disseminate information about corporate misconduct at an early stage and has been considered in the past as the most informative communication tool and effective watchdog for retail investors (Miller, 2006). Even local presses monitor corporate misconduct of publicly listed firms. Heese, Pérez-Cavazos, and Peter (2022) show that firm corporate misconduct significantly increases when the local newspaper leaves town, indicating that local newspapers are an important monitor of corporate misconduct.

3.2 The social media as a monitor of corporate misconduct

While the traditional media has declined during recent decades, social media has become a fast-growing channel to share information publicly. Social media are often more engaging than traditional media because the social media encourage more active interactions. Previous studies document that social media provide platforms for investors to share information about firms and make investment decisions (e.g., Chen, De, Hu, and Hwang, 2014; Bartov, Faurel, and Mohanram, 2018; Cookson and Niessner, 2020; Chen and Hwang, 2022) and disseminate value-relevant information.

The role of social media in monitoring corporate misconduct has empirical support. For example, using the staggered introductions of 3G mobile broadband access in the U.S. as an exogenous shock, Heese and Pacelli (2023) find that high social media involvements in areas where firm facilities are located are associated with reduced corporate misconduct. By examining misleading information about one corporate misconduct (Empowered Products Inc.) posted on the Social Studio, Xiong, Chapple, and Yin (2018) find that social media can be used for corporate misconduct detection using an aggregation of the dispersed information (wisdom) of the crowds. Dong, Liao, and Zhang (2018) successfully use machine learning techniques to extract misconduct signals from 64 firms.

3.3 Motivation for the relation between social media and corporate misconduct

According to Becker's (1968) crime theory, firms are less likely to engage in corporate misconduct if expected costs of committing misconduct are greater than the expected benefits. Since the social media spread news more quickly and to a wider audience than traditional media, social media can increase the probability that the audience will receive news about corporate misconduct. In turn, this can increase expected reputational costs (Dyck, Volchkova, and Zingales, 2008; Heese and Pacelli, 2023). A recent study provides supporting evidence that small-investor communications with firms through China's online interactive platforms raise reputation costs (Li, Wang, and Zhang, 2023b).

However, one could argue that China's quasi-social media posts may not diminish the incidence of corporate misconduct. First, viral web communications are generally short lived (Heese and Pacelli, 2023). Second, it is hard to evaluate whether negative posts disclose firm misbehavior (Heese and Pacelli, 2023) or just negative venting against firms for a variety of reasons, such as losses on current share positions in the firm or to reap a profit on a short position. Therefore, whether investor-initiated communications with firms through China's online interactive platforms reduce the incidence of corporate misconduct is an empirical question.

4. Data and Summary Statistics

We collect corporate misconduct data from the China Stock Market and Accounting Research (CSMAR) database. We follow Li, Makaew, and Winton (2020) and Zhang (2018) to eliminate minor misdemeanors from the rule-violation events.[7] We then retrieve the year of misconduct from penalty data. The data on investor-initiated communications on the two online platforms are collected from the Chinese Research Data Services Platform. The data contain the raw interaction information from the *Easy Interaction* and *E-Interaction* online platforms launched by the Shenzhen and Shanghai Stock Exchanges, respectively.[8] We then program using Python to clean the data and construct our key variables of interest on the investor-initiated communications.

Based on the Guidelines for the Industrial Classification of Listed Companies, our industry classification includes 18 main industries excluding the financial industries. Since the manufacturing industry is the biggest industry in China spanning 29 different subindustries and accounts for more than half of all listed companies, we use 3-digit industry subcategories to identify each firm in the manufacturing industry (Wu, Johan, and Rui, 2016; Zhang, 2018). Our panel data consist of 3,484 misconduct firms and 16,494 firm-year observations.

The dependent variable *Misconduct* is an indicator variable equal to one if a firm commits misconduct. To measure interactions between investors and firms, we use the number of questions asked by investors or the responses made by firms that are collected by the Chinese Research Data Services Platform. *Question number* is defined as the natural logarithm of one plus the total number of questions that investors asked on a firm's interactive platform in a year. *Reply number* is defined as the natural logarithm of one plus the total number of replies made by a firm in a year. The alternative measures of investor communications are *Reply ratio*, *Reply interval*, *Reply length,*

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[7] We first select firms in CSMAR that have a "Yes" response to the item "whether the listed firm violated the rules". We then filter out firms that did not receive a "letter of monitoring". A letter of monitoring is one type of monitoring announced by regulatory authorities for a firm's misdemeanor.

[8] The respective websites for *Easy Interaction* and *E-Interaction* platforms by the Shenzhen and Shanghai Stock Exchanges are http://irm.cninfo.com.cn/ircs/index and http://sns.sseinfo.com/.

Question sentiment, and *Reply sentiment*. The definitions of these variables are provided in the Appendix and in the following sections.

We include firm-, institutional-, governance-, and trading-characteristics as control variables. The definitions of all control variables follow the literature (e.g., Khanna, Kim, and Lu, 2015; Wang, 2013; Wang, Winton, and Yu, 2010; Zhang, 2018). Namely, *Firm age* is measured by the number of years since the inception of a firm. *Firm size* is the logarithm of total assets. *Financial leverage* is measured by total liabilities divided by total assets. *Growth rate* is the percentage increase of revenues. *Tobin's Q* is the market value of assets divided by the book value of assets. *State-owned enterprise* is a dummy variable that equals one if a firm is a state-owned enterprise and zero otherwise. The institutional-specific variables are *ownership concentration*, which is the sum of the shareholding ratio of the top five shareholders, and *institutional shareholding ratio*, which is the sum of the shareholding ratios of the institutional shareholders. We include internal corporate governance related control variables because governance is closely linked to corporate misconduct (Khanna, Kim, and Lu, 2015). *Independent director* is the number of independent directors divided by total number of directors. *Board size* is the logarithm of one plus the number of directors on the board. *Board meetings* is the logarithm of one plus the number of board meetings. *CEO duality* is an indicator variable that takes the value of one if the company's CEO and the board chairman are the same person and zero otherwise. The trading-characteristics variables are *stock turnover, return,* and *volatility* (Jones and Weingram, 1996; Wang, 2004). *Stock turnover* is the number of shares traded in a year divided by the number of shares outstanding. *Stock return* is the percent stock price change over a year. *Stock volatility* is the standard deviation of daily stock returns over a year. We also control for the auditor quality of a firm. If a firm's auditor is one of the Big Four international accounting firms, the firm's disclosure quality may be higher (Mitton, 2002). These Big Four are Deloitte, PricewaterhouseCoopers (PwC), Ernst & Young, and KPMG. The presence of a Big Four as auditor can significantly reduce the incidence of corporate scandals since stringent audits can protect shareholders (Chen, 2016). *Auditor quality* *is* equal to one if a firm is audited by one of the Big Four international accounting firms, and zero otherwise.

Table 1 presents the summary statistics of the main variables used in this study. The mean and standard deviation of our dependent variable *Misconduct* is 0.167 and 0.372, respectively. The distribution of our misconduct measure is in line with previous studies (e.g., Xiong, Chapple, and Yin, 2018; Kryzanowski, Li, Xu and Zhang, 2021). The average natural logarithm of one plus questions asked by investors (*Question number*) and replies made by firms (*Reply number*) is 4.19 and 3.99, respectively. The average reply ratio is 0.882 with a standard deviation of 0.25. This indicates that a firm, on average, answers 88.2% of questions asked by investors.

[Please Place Table 1 about Here]

5. Empirical Tests

5.1 Baseline regression

We use the following basic probit regression model to examine whether the online investor-initiated communications with firms is associated with the incidence of corporate misconduct:

$$\begin{aligned} Pr\left(Misconduct_{i,t}\right) = \beta_0 + \beta_1 Communication_{i,t-1} + \gamma Controls_{i,t-1} \\ + Industry\ FE_i + Province\ FE_i + Year\ FE_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where subscripts *i* and *t* stand for firm and year. *Misconduct* is an indicator variable equal to one if a firm commits misconduct and zero otherwise. Our main independent variable of interest *Communication* captures investor-initiated interactions with firms. It is measured by the natural logarithm of one plus the total number of questions asked by investors (*Question number*), or the natural logarithm of one plus the total number of replies made by firms (*Reply number*). *Controls* denotes a set of firm-, institutional-, governance-, and trading-characteristics, as discussed in Section 2, which are measured in year *t-1*. We control for industry, province, and year fixed effects. The standard errors are clustered at the firm level.

Table 2 reports the probit regression results over the period from 2014 through 2020. The coefficients of *Question number* and *Reply number* are significant and negative at -0.050 and

-0.054, respectively. Economically, one-standard-deviation increases in the logarithm of the number of questions asked by investors and replies made by firms are associated with a reduction of the probability of the incidence of misconduct by 6.2% and 7.7%, respectively. This indicates that investor-initiated interactions can significantly reduce the probability of the incidence of misconduct. These findings support the conjecture that investor-initiated interactions are more likely to be associated with a reduction in the incidence of corporate misconduct.

[Please Place Table 2 about Here]

Since only detected misconduct is observed, our measure of misconduct in the previous section may suffer from measurement bias. We follow Wang (2013) and use a bivariate probit model to address this concern. However, our bivariate probit model does not converge. Nonconvergence is a problem encountered when implementing bivariate probit models with partial observability (Farber, 1983; Heywood and Mohanty, 1994, Gong and Johnson, 2021). This is encountered and noted in some corporate misconduct studies (e.g., Zhang, 2018; Karpoff, Lee, and Martin, 2014).

5.2 Difference-in-differences (DiD) test

To further identify a causal relation between investor-initiated interactions and corporate misconduct, we use the establishment of the *Easy Interaction* platform by the Shenzhen Stock Exchange in 2010 as an exogenous shock to the interactions between investors and firms. *Easy Interaction* was launched by the Shenzhen Stock Exchange on January 1, 2010, while *E-Interaction* was launched by the Shanghai Stock Exchange on July 4, 2013.

The staggered adoption of the two investor interactive platforms creates a unique setting for the DiD test. For the launch of the interactive platform by the Shenzhen Stock Exchange in 2010, the post-event period is 2010-2012 [9] and the pre-event period is 2008 and 2009. The treated firms are those listed in the Shenzhen Stock Exchange and the control firms are those listed in the Shanghai Stock Exchange. This DiD specification is the same as in Lee and Zhong (2022). We use the nearest

[9] Since the Shenzhen Stock Exchange launched its interactive platform on January 1, 2010, we define 2010 as being in the post-event period. However, our DiD result is robust to the post-event period only including 2011 and 2012.

neighbor propensity score matching (PSM) approach to match each treated firm with a control firm. Specifically, we estimate the logit model for the treated and control firms in 2009, one year prior to the launch of *Easy Interaction* by the Shenzhen Stock Exchange. In the logit model, the dependent variable *Treat* equals 1 if a firm is a treated firm that is listed on the Shenzhen Stock Exchange in 2009 and 0 if a firm is a control firm that is listed on the Shanghai Stock Exchange. The control variables are all the variables used in our previous baseline regression test, including firm, institutional, and governance characteristics. The balance test results shows that there is no significant difference between treated and control groups after the PSM matching. We end up with 598 firms with misconduct and 2,981 firm-year observations over the period from 2008 to 2012.

Our DiD methodology is implemented by estimating the following probit model:

$$\begin{aligned} Pr(Misconduct_{i,t}) \\ &= \alpha + \beta_1 Treat_i \times Post_t + \beta_2 Treat_i + \gamma_1 Controls_{i,t-1} \\ &+ \gamma_2 Controls_{i,t-1} \times Post_t + Industry\ FE_i + Province\ FE_i \\ &+ Year\ FE_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where *i* and *t* refer to firm and year, respectively. The dependent variable *Misconduct* is an indicator variable equal to one if a firm has committed misconduct. *Treat* is a dummy variable equal to one for treated firms, and 0 for control firms discussed earlier. *Post* is a dummy variable equal to one for the post-event years, 2010, 2011, and 2012, and zero for the pre-event years, 2008 and 2009. *Controls* is a set of variables controlling for firm-, institutional-, governance-, and trading-characteristics. Treated and control firms could differ in various dimensions that might be correlated with the outcome variables and hence bias the estimates upward or downwards (Barrot, 2016). To address this issue, we follow Barrot (2016), amongst others, by interacting the firms' control variables with the *Post* dummy. We include industry, province, and year fixed effects.[10] The standard errors are clustered at the firm level. The coefficient on the interaction term $Treat \times Post$ captures the effect of the introduction of *Easy Interaction* by the Shenzhen Stock

[10] We do not add the *Post* dummy as it is absorbed by the year fixed effects.

Exchange at the beginning of year 2010 on corporate misconduct.

Table 3 presents the DiD regression results between 2008 and 2012 based on the probit model including and excluding the interaction terms between the control variables and the post dummy for the matched samples in columns (1) and (2), respectively. The coefficients on the interaction term $Treat \times Post$ are negative and significant in both columns. The economic magnitude is also sizable. The estimated coefficients of -0.293 in column (1) and -0.264 in column (2) indicate that the treatment group experiences a decrease of 11.9% and 10.8% in the incidence of misconduct, respectively, compared to the control group after the launch of *Easy Interaction* in 2010. The results indicate that treated firms are more likely to reduce the incidence of corporate misconduct than control firms. The results further suggest that investor-initiated interactions are more likely to reduce the incidence of corporate misconduct.

[Please Place Table 3 about Here]

5.3 Parallel trend analysis

The key identifying assumption in the DiD estimation is that treatment and control firms share parallel trends prior to the launch of *Easy Interaction* by the Shenzhen Stock Exchange. To support the parallel-trend assumption, we follow the method in Atanassov (2013), Gao and Zhang (2019), and Kong, Zhang, and Zhang (2022), amongst others, to examine the dynamics of corporate misconduct prior and post to the launch of *Easy Interaction* in the following probit model:

$$\begin{aligned} Pr\ (Misconduct_{i,t}) \\ &= \alpha + \beta_1 Treat_i \times Before_{i,t}^{-2} + \beta_2 Treat_i \times Current_{i,t}^{0} \\ &+ \beta_3 Treat_i \times After_{i,t}^{1} + \beta_4 Treat_i \times After_{i,t}^{2} + \beta_5 Treat_i \\ &+ \gamma_1 Controls_{i,t-1} + \gamma_2 Controls_{i,t-1} \times Post_t + Industry\ FE_i \\ &+ Province\ FE_i + Year\ FE_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where $Before^{-2}$ is an indicator variable equal to one if the observation is in the period two years prior to the *Easy Interaction* launch, which is the year 2008 and zero otherwise. $Current^{0}$ is the indicator equal to one if the observation is in the year (2010) of the *Easy Interaction* launch and zero otherwise. $After^{1}$ and $After^{2}$ are indicator variables that are equal to one if the observation is in the first (2011) and second (2012) years after the *Easy Interaction* launch and zero otherwise. We use $Before^{-1}$ as the reference year (2009), which is one year prior to the initiation of *Easy Interaction*. Therefore, it does not appear in the equation of the parallel trend analysis. All the other variables are defined as in the Appendix. The standard errors are clustered at the firm level. The coefficient on the interaction term $Treat \times Before^{-2}$ determines whether treated firms and control firms have a pre-trend in the incidence of corporate misconduct. The dynamic DiD regression results reported in Table 4 show that the coefficients on $Treat \times Before^{-2}$ are not significantly different from zero, but the coefficients on the interaction terms $Treat \times After^{1}$ and $Treat \times After^{2}$ are significantly negative. This suggests that the parallel trend assumption of DiD holds, and that the incidence of corporate misconduct decreases after the launch of *Easy Interaction* but not before. The trend of the incidence of corporate misconduct is consistent with our results for the DiD regression, strengthening our finding that the launch of *Easy Interaction* reduces the incidence of corporate misconduct.

[Please Place Table 4 about Here]

Figure 1 presents the coefficient estimates on the interaction terms in column (1) of Table 4 with 95% confidence intervals based on the dynamic DiD regression (3). The coefficient estimates are statistically significant for years after 2010 but not before. The evidence suggests that trends in the likelihood of corporate misconduct prior to the initiation of interactive platforms are the same for the treated and control samples, but change significantly following the initiation of the interactive platform due to the drop for the treated firms. These findings support the validity of the parallel trend assumption.

[Please Place Figure 1 about Here]

5.4 Placebo tests

It is possible that our DiD estimations are purely driven by chance. To address this issue, we conduct two placebo tests. First, we assume the launch year of *Easy Interaction* to be in 2009, one year prior to 2010. Specifically, the sample period is from 2007 to 2011 when the pseudo-platform introduction is assumed to be in 2009. Table 5 reports the results of this placebo test including and excluding all the control variables interacted with the indicator *Post*. We do not find significantly negative coefficients for the interaction terms for both columns of Table 5.

[Please Place Table 5 about Here]

Second, we randomly choose 595 pseudo treated firms from the year of 2009, where the number of pseudo-treated firms is the same as that for our DiD regression (2), and the rest of the pool of firms is used as the pseudo-control firms. Using these pseudo-treated and control firms, we re-estimate the DiD regression (2) and save the coefficients and *z*-values for the interaction term *Treat* × *Post*. We repeat this procedure 5,000 times. Figure 2 plots the distribution of pseudo *z*-values for *Treat* × *Post.* The *Z*-value for the estimated DiD coefficient of *Treat* × *Post* reported in column (1) of Table 3 is -2.347, which is located on the left side of the estimated pseudo z-value distribution. Since only 1.56% (78 out of 5,000) pseudo z-values are smaller than the actual z-value (-2.347) for the DiD estimated coefficient of the interaction variable, the pseudo results lend further support that our DiD results may not be driven by luck.

[Please Place Figure 2 about Here]

Overall, the two placebo test results indicate that our DiD test results are associated with the initiation of the *Each Interaction* platform by the Shenzhen Stock Exchange in 2010. Thus, it is unlikely to be driven by change.

6. Additional tests using alternative measures of interactions

6.1 Alternative measures of reply

We define three alternative measures of the replies of firms. The first variable *Reply ratio* is defined as the ratio of the number of questions replied to the number of total questions asked. The second variable *Reply interval* is measured by the logarithm of one plus the average number of days between when the question is asked and replied to. If questions are not answered, the number of days is considered as a missing value rather than zero.

The third variable *Reply length* is the logarithm of one plus the average number of words in each reply made by a firm over a year. Prior study documents that word counts can be used to measure information transparency. Kryzanowski and Mohebshahedin (2020) find that the average number of words in board disclosures of advisory contract renewals by closed-end funds can measure transparency of fund board activities in approving the renewal of advisory contracts on the monitoring behavior of fund directors. Given this evidence, we expect that firms provide or clarify more information and become more transparent when their replies include more words. In turn, this reduction in information asymmetry (Gelos and Wei, 2002) lowers the incidence of corporate misconduct.

We estimate the baseline regression (1) by replacing *Reply number* with the three alternative measures of reply, *Reply ratio*, *Reply interval,* and *Reply length*. Table 6 reports the estimated results. We find that the coefficient on *Reply ratio* in column (1) is significantly negative and the coefficient on *Reply interval* in column (2) is significantly positive. These results indicate that there is less corporate misconduct when the response ratio is higher or the response interval is shorter. The coefficient on *Reply length* in Column (3) is significantly negative, indicating that increased word counts of replies are associated with less corporate misconduct. As expected, by providing more information to inquisitive investors, firms are less likely to commit misconduct when they make greater efforts to reduce informational asymmetry.

[Please Place Table 6 about Here]

6.2 Sentiment extracted from investor-initiated interactions

The negative sentiment of investors may influence firm performance or investment strategies. Negative comments capture outside investors' attention and encourage firm management to rectify their potential misbehavior (Li, Wang, and Zhang, 2023b). Chen, De, Hu, and Hwang (2014) find that aggregated negative tones of investors expressed on the social media (Seeking Alpha) negatively predict stock returns and earnings surprises. Ang, Hsu, Tang, and Wu (2021) find that small investors' criticisms on the social media predict the likelihood of the withdrawal of valuedestroying acquisitions by managers. Li, Wang, and Zhang (2023b) find that firms receiving more negative sentiments from China's online interactive platforms deters more earnings management. Thus, we expect that retail investors' negative sentiment incorporated in interactions between retail investors and firms can help to predict the reduction of corporate misconduct propensity.

To test the relation between investor-initiated interactions and corporate misconduct, we extract the sentiment content from questions made to or replies by a firm. The sentiment ratio for questions (replies) is calculated by using the Python library of sentiment analysis for simplified Chinese with respect to SnowNLP.[11] The scale of the sentiment ratio is between 0 and 1, ranging from the saddest to happiest sentiment. We average all the sentiment ratios of a firm over a year with respect to questions or replies and then split the sample in terciles based on the average sentiment ratios for questions and replies over a year. The average sentiment for questions and replies for negative, neutral, and positive sentiment subsamples are 0.279, 0.400, and 0.519; and 0.520, 0.696, and 0.847, respectively. We estimate the baseline probit regression (1) for each subsample by replacing the independent variable of interest *Interaction* with *Question sentiment* or *Reply sentiment*. The coefficients on *Question sentiment* and *Reply sentiment* for the negative-tone subsamples reported in Columns (1) and (4) of Table 7, respectively, are significantly negative. As expected, the negative sentiment incorporated in investors' questions and firms' replies can predict a low incidence of corporate misconduct. The results are consistent with the finding by Li, Wang, and Zhang (2023b) who find that negative comments by retail investors deter firms' earnings management. In contrast, the estimated coefficients on *Question sentiment* in Column (3) and *Reply sentiment* in Column (6) for the positive sentiment subsample are significantly positive and

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[11] NLP is a short name for Natural language processing. This subfield of linguistics, computer science, information engineering, and artificial intelligence focuses on the interactions between computers and human (natural) languages, specifically processing and analyzing huge amounts of natural language data by using computer programming. The reference is available at: https://medium.com/analytics-vidhya/python-snownlp-sentiment-analysis-for-the-chinese-language-8d9cafd0447d. The NLP techniques have been used to extract information from textual contents from posts on social media such as Stocktwits.com (Massa, Zhang and Dong, 2015; Renault, 2017; Nekrasov, Teoh and Wu, 2022).

insignificant, respectively. The results suggest that positive tones embedded in replies can predict a higher incidence of corporate misconduct. A plausible explanation for the positive relation between investor questions with positive sentiment and the incidence of corporate misconduct is that such questions indicate a less effective governance or monitoring role by investors which facilitates corporate misconduct.

[Please Place Table 7 about Here]

7. Possible channel and confounding effects

7.1 Information asymmetry

By disseminating more information to investors rather than relying solely on third-party intermediaries, social media interactions alleviate information asymmetry (Blankespoor, Miller, and White, 2014). Lee and Zhong (2022) find that China's online interactive platforms reduce information asymmetry, as direct communications with firms' managements help retail investors to understand and process information that are released by firms. Li, Wang, and Zhang (2023b) find that information asymmetry works as a channel through which online communications initiated by investors deter earnings management. Thus, given that investor-initiated online communications are associated with less information asymmetry, or equivalently more transparent information disclosure (Gelos and Wei, 2002), we expect the incidence of corporate misconduct will be reduced through this channel.

We use two metrics to measure information asymmetry. First, we use dispersion in analyst earnings forecasts as a proxy for information asymmetry, where the absolute difference between the mean of forecast earnings per share and actual earnings per share is scaled by stock price at the beginning of the year (e.g., Platikanova and Mattei, 2016; Zhang, 2006). Thus, high dispersion in analyst earnings forecasts indicates high information asymmetry. We divide our sample into two subsamples based on the industry median of dispersion in analyst earnings forecasts. We then re-estimate the baseline regression (1) for each subsample. Panel A of Table 8 reports the regression results. The coefficients of *Question number* and *Reply number* for the subsamples of high and low dispersion in analyst earnings forecasts are significantly negative and insignificant, respectively. The differences in the coefficients of *Question number* or *Reply number* for the subsamples of high and low dispersion in analyst earnings forecasts are significant. The *p*-values of the χ^2 for the coefficient comparisons between columns (1) and (2), or between columns (3) and (4) are 0.0139 and 0.0637, respectively. This indicates that investor-initiated online communications are associated with a reduction in the propensity of corporate misconduct only for firms with high information asymmetry.

[Please Place Table 8 about Here]

Second, we follow Li, Wang, and Zhang (2023b) and Huang, Huang, and Lin (2019) and measure information asymmetry using stock price synchronicity. Stock price synchronicity measures the extent to which stock price fluctuations are explained by market and industry benchmarks. Stock price synchronicity is calculated from the CSMAR, where it is calculated as the adjusted R^2 obtained by regressing a firm's stock return on market and industry benchmarks. Then stock price synchronicity (adjusted R^2) is transformed to a normal distribution by $\ln(R^2/(1-R^2))$. A higher stock price synchronicity indicates lower firm-specific news embodied in the stock price, which represents higher information asymmetry. We split our sample into high- and low-information asymmetry based on the industry median of stock price synchronicity. We rerun the baseline regression (1) for each of the two subsamples. Panel B of Table 8 reports the regression results. The coefficients of *Question number* or *Reply number* for the subsample of high stock price synchronicity reported in columns (2) and (4) are negative and significant, while the coefficients for the subsample of low information asymmetry reported in columns (1) and (3) are negative but insignificant. These results also indicate that online interactive communications initiated by retail investors are more likely to reduce the incidence of corporate misconduct only for firms with high information asymmetry.

7.2. Internal corporate governance

A well-established and implemented internal control system can improve the quality of financial reporting and strengthen internal management (Ji, Lu, and Qu, 2017). Through its five components (control environment, risk assessment, control activities, information, and communication) and monitoring, effective internal control can maintain the stability of capital markets and alleviate stock price crash risk (Chen, Chan, and Dong et al., 2017). In contrast, poor internal control management can lead to large management forecasting errors (Feng, Li, and McVay, 2009) and misconduct (Donelson, Ege and McInnis, 2017; Zakaria, Nawawi, and Salin, 2016). Donelson, Ege, and McInnis (2017) find that internal control weaknesses provide a general opportunity for managers to commit misconduct, and helps to predict the incidence of corporate misconduct. Thus, a firm with high-quality internal controls is less likely to commit misconduct. Thus, one may argue that our baseline results that investor-initiated interactions are related to a reduction in the incidence of corporate misconduct may be due to a firm's good internal controls rather than investor-initiated interactions.

We collect the internal control index for a firm each year from the DIB database. A high index value represents good internal control quality. To determine if our baseline results are caused by good internal control and not investor-initiated interactions, we partition the sample into good- and bad-internal control subgroups, based on the industry median of the internal control indexes in a year. We re-estimate the baseline regressions for the good- and bad-internal control quality subsamples. All the estimated coefficients on *Question number* and *Reply number* reported in Table 9 are significantly negative, but once again there is no significant difference between the coefficients on *Question number* and *Reply number*, as indicated by the *p*-values of the Chi-square statistics. These results suggest that high internal control quality does not modify our baseline finding of a negative relation between investor-initiated interactions and the incidence of corporate misconduct.

[Please Place Table 9 about Here]

7.3 External corporate governance

7.3.1 Print media coverage

Press media are important instruments for monitoring the behavior of firms by reducing information asymmetry (Bushee, Core, and Guay, 2010) and improving accountability. Press media serve as public "watchdogs" in monitoring management activities. Prior studies find that media reporting can deter managers from engaging in opportunistic insider trading activities (Dai, Parwada, and Zhang, 2015), curb managers' earnings management incentives, and can even substitute for other monitoring agents, such as auditors and boards of directors, when financial analysts are ineffective (Chen, Cheng, Li, and Zhao, 2021). Local press can also monitor firms' wrongdoings, and local newspaper closures increase firm misconduct (Heese, Pérez-Cavazos, and Peter, 2022). Since media coverage enhances firms' visibility (Miller, 2006) and attracts retail investors' attention (Fang and Peress, 2009), it is possible that a lower incidence of corporate misconduct is attributable to more media coverage rather than to the monitoring effect of investor-initiated communications on interactive platforms.

To explore the mediating effect of press media, we obtain print media coverage data from the Chinese Research Data Services (CNRDS). *Print media coverage* is the natural logarithm of one plus total number of newspaper headlines about a firm (Xu, Xuan, and Zheng, 2021; Fu and Qi, 2021). We split our sample into high- and low-media coverage groups according to the industry median value of media coverage over a year. Table 10 reports the impact of media coverage for the two subsamples based on the baseline regression (1). The estimated coefficients on *Question number* and *Reply number* are negative and significant for the high- and low-media subsamples in all specifications, and no significant differences in the coefficients are found between the two subsamples as the *p-values* of the Chi-squares are greater than 10%.[12] The results suggest that the

[12] Our result is robust to the use of a measure of *web media coverage* defined as the natural logarithm of one plus the total number of web news headlines about a firm. The untabulated table is available upon request.

negative effect of investor-initiated interactions on the incidence of corporate misconduct remains whether media coverage is high or low.

[Please Place Table 10 about Here]

7.3.2 Internet searching index

The internet has become an important information intermediary in disseminating public information to investors. Prior studies find that internet search volume measures internet search behavior of the general population and captures the attention of retail investors (Da, Engelberg, and Gao, 2011). Retail investors use internet searches to acquire public information that has not yet been fully incorporated into prices. Retail investors search for public information in case of an important corporate event, particularly earnings announcements (Drake, Roulstone, and Thornock, 2012). Investor attention reduces earnings management (Hirshleifer and Teoh, 2003; Jin, 2013), and consequently, management has lower incentives to misrepresent firm performance, mislead stakeholders or affect contractual outcomes (Healy and Wahlen, 1999). The search behavior of retail investors could differ if given the opportunity to obtain information directly from firms using investor-initiated communications on an interactive platform. As a result, retail investors may use only one or both sources of information, and the effect of internet searching on our baseline relation is an empirical question.

We use the Baidu search index of a firm to represent the Internet search index, as Baidu is the biggest Internet search company in China. We partition our sample into high-searching and low-searching volume if a firm's annual average search volume is above or below the industry median in a year. We re-estimate our baseline regressions for the two subsamples. Table 11 reports that all the estimated coefficients on *Question number (Reply number*) are significantly negative for high- and low-searching samples, and the difference in the coefficients between the two subsamples is insignificant as the *p*-values of the Chi-squares are greater than 10%. These results suggest that internet searching does not eliminate the negative relation between investor-initiated interactions and the incidence of corporate misconduct that we previously identified.

[Please Place Table 11 about Here]

8. Effect of investor-initiated interactions on firm value

Prior studies find that information disseminated on a social media platform helps investors to make investment decisions. By uncovering additional value-relevant information, social media improves market efficiency, so that the aggregate opinion transmitted through social media successfully predicts firm performance (e.g., Bartov, Faurel, and Mohanram, 2018; Chen, De, Hu, and Hwang, 2014). On the other hand, although online investor-initiated interactions are associated with a reduction in the incidence of corporate misconduct, it is unclear whether the benefits outweigh the costs of interactions in which managers tend to satisfy inquisitive retail investors by strengthening firm internal controls or hiding misconduct at the expense of firm value.

To investigate the association of firm values in the concurrent and subsequent year with the questions asked by retail investors and responses made by firms, we use Tobin's Q as a proxy of firm market value by following the literature in corporate governance (e.g., Bebchuk and Cohen, 2005; Servaes and Tamayo, 2013; Bardos, Ertugrul, and Gao, 2020; An and Liu, 2023). We run the OLS regression of *Tobin's Q* in the current and following year on *Question number* and *Reply number*, respectively. Table 12 reports the estimated results. We find that the coefficients on *Question number* and *Reply number* are significantly positive for Tobin's Q for the current and following year.[13] One-standard-deviation increases in *Question number* and *Reply number* are associated with increases of 9.17% and 5.52%, and 3.33% and 2.36% in *Tobin's Q* in the concurrent and following year of the investor-initiated interactions, respectively.

The results indicate that the activity levels on the online investor-initiated exchange platforms are associated with higher market valuations. Overall, the online investor-initiated interactive platforms provide value benefits for firms. This may be due to the reduction of information asymmetry by the interactive platforms (Lee and Zhong, 2022).

[13] The result is robust to using industry-adjusted Tobin's Q, measured as Tobin's Q minus the median Tobin's Q in the industry.

[Please Place Table 12 about Here]

9. Conclusion

We examine the relation of retail investors' interactions with the incidence of corporate misconduct. Using China's investor-initiated interactive platforms, we find online investor-initiated interactions are more likely to reduce the propensity of corporate misconduct. The finding is robust to identification concerns and alternative measures of investor-initiated interactions. We find that firms with high information asymmetry are more likely to reduce the propensity of corporate misconduct while internal and external corporate governance monitoring does not negate the negative relations between such interactions and the incidence of misconduct. We also find that investor-initiated interactions can significantly enhance a firm's value in the year of and the year after the online platform interactions occur between investors and firms.

Our findings have important implications for policymakers, investors, and firms. For policymakers and regulators, our results indicate the importance of the monitoring role of social media with the growth of internet technology. Regulators can monitor the information generated by investors using internet technology to better detect and prevent misconduct practices in capital markets. For retail investors, our findings imply that online interactive platforms enable them to acquire more accurate and clear information, and consequently, may help to protect minority shareholders. For firms, our findings indicate that investor-initiated interactions can serve as a "watchdog" for monitoring corporate misconduct, while providing a potential benefit in terms of increased firm value.

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Appendix: Variable descriptions

This table provides definitions of all the variables. All the variables are measured for a firm in a given year.

Variables	Definition
Dependent variables	
Misconduct	The indicator variable equals one if a firm commits misconduct and zero otherwise.
Independent variables of interest	
Question number	The natural logarithm of one plus the total number of questions that investors asked on a firm's interactive platform.
Reply number	The natural logarithm of one plus the total number of replies made by a firm in a year.
Reply ratio	The number of responses divided by the number of questions for a firm in a year.
Reply interval	The natural logarithm of one plus the average number of days between a question asked and replied to in a year. If questions are not answered, the number of days is considered as a missing value rather than zero.
Reply length	The natural logarithm of one plus the average number of words per reply by a firm in a year.
Question sentiment	The average sentiment ratio for all the questions investors asked on a firm's interactive platform. The sentiment ratio per question is calculated by using the Python library for sentiment analysis of questions in simplified Chinese using SnowNLP. The range of this ratio is between 0 (lowest sentiment) and 1 (highest sentiment).
Reply sentiment	The average sentiment ratio for all the responses made by a firm. The sentiment ratio per reply is calculated by using the Python library for sentiment analysis of replies in simplified Chinese using SnowNLP. The range of this ratio is between 0 (lowest sentiment) and 1 (highest sentiment).
DiD variables	
Treat	Treatment group is based on an indicator variable that equals one if the firm is listed in the Shenzhen Stock Exchange one year prior to the interactive platform launched by this exchange in 2010. Control group is based on an indicator variable equal to zero if the firm is listed in the Shanghai Stock Exchange and has been one-to-one nearest neighbor propensity score matched (PSM) with a treatment firm for the year 2009.
Post	An indicator variable that equals one for 2010-2012 period, and zero for the 2008-2009 period.
Control variables	
Firm age	The number of years since the inception of a firm.
Firm size	The logarithm of total assets.
Financial leverage	Total liabilities divided by total assets.
Growth rate	The difference between the revenues of the current period minus

	that of the previous period divided by the revenues of the previous period.
Tobin's Q	Market value of assets divided by the book value of assets.
Stated-owned enterprise	An indicator variable that takes the value of one if a firm is a state-owned enterprise and zero otherwise.
Ownership concentration	Sum of the shareholding ratio of the top five shareholders.
Institutional shareholding ratio	Sum of the shareholding ratios of the institutional shareholders.
Independent director	The number of independent directors divided by the total number of directors.
Board size	The natural logarithm of one plus the number of directors on the board.
Number of board meetings	The natural logarithm of one plus the number of board meetings held.
CEO duality	An indicator variable that takes the value of one if the company's CEO and board chairman are the same person and zero otherwise.
Audit quality	An indicator variable that takes the value of one if a company's auditor is one of the Big Four international accounting firms, Deloitte, PricewaterhouseCoopers (PwC), Ernst & Young, and KPMG and zero otherwise.
Stock turnover	The number of shares traded in a year divided by the number of shares outstanding.
Stock return	The stock price change over a year in percent.
Stock volatility	The standard deviation of daily stock returns over a year.

Figure 1. Coefficient plot for treated and control firms for the dynamic DiD test

This figure plots the estimated coefficients on the dummy variable *Year* in Eq. (3) with 95% confidence intervals from 2008 to 2012. The reference event year is 2010.

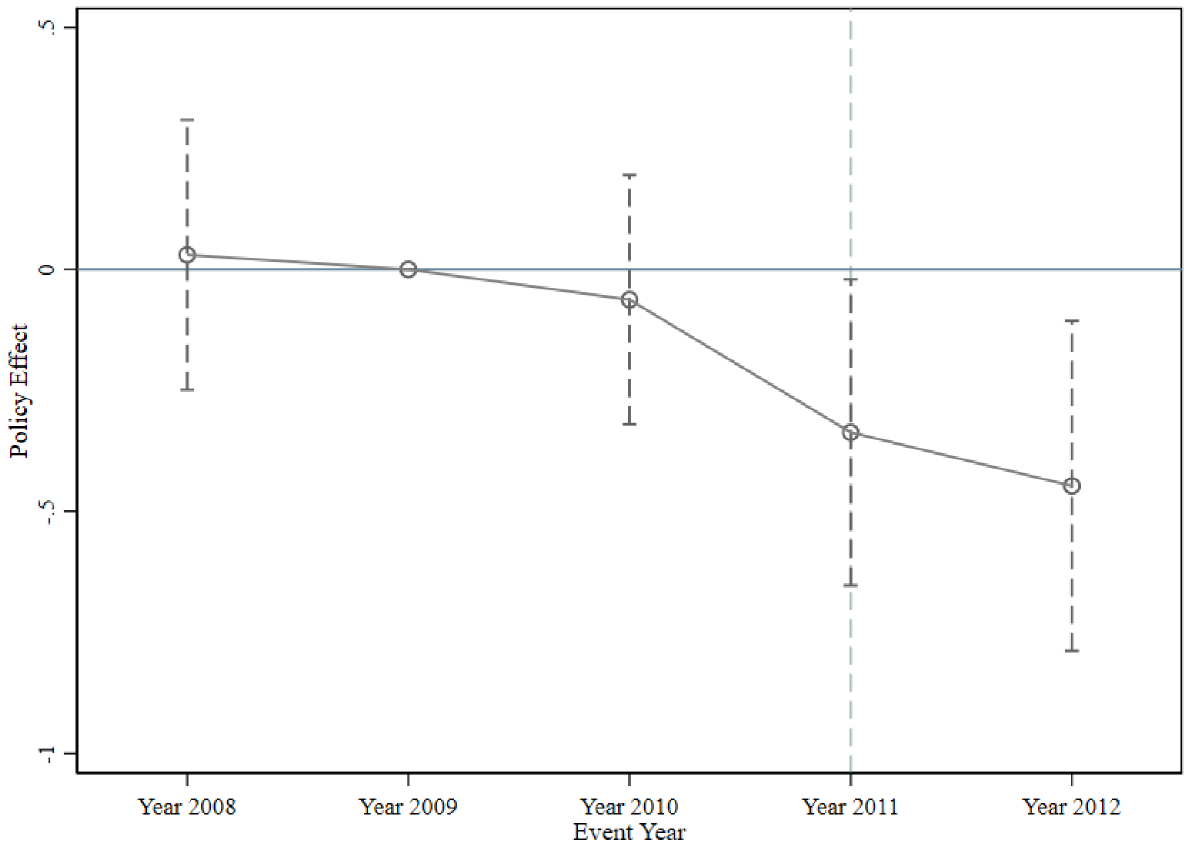

Figure 2. Placebo test

This figure plots the distribution of pseudo *z*-values for *Treat* × *Post* from 5,000 bootstrap simulations. We randomly choose a sample of 595 pseudo treated firms from the year of 2009, the same number of observations as those used for the DiD regression, and the remaining pool of firms is used as pseudo-control firms. Based on these pseudo-treated and control groups, we re-estimate the DiD regression as in column (2) of Table 3 5,000 times, and save the *z*-values for *Treat* × *Post*.

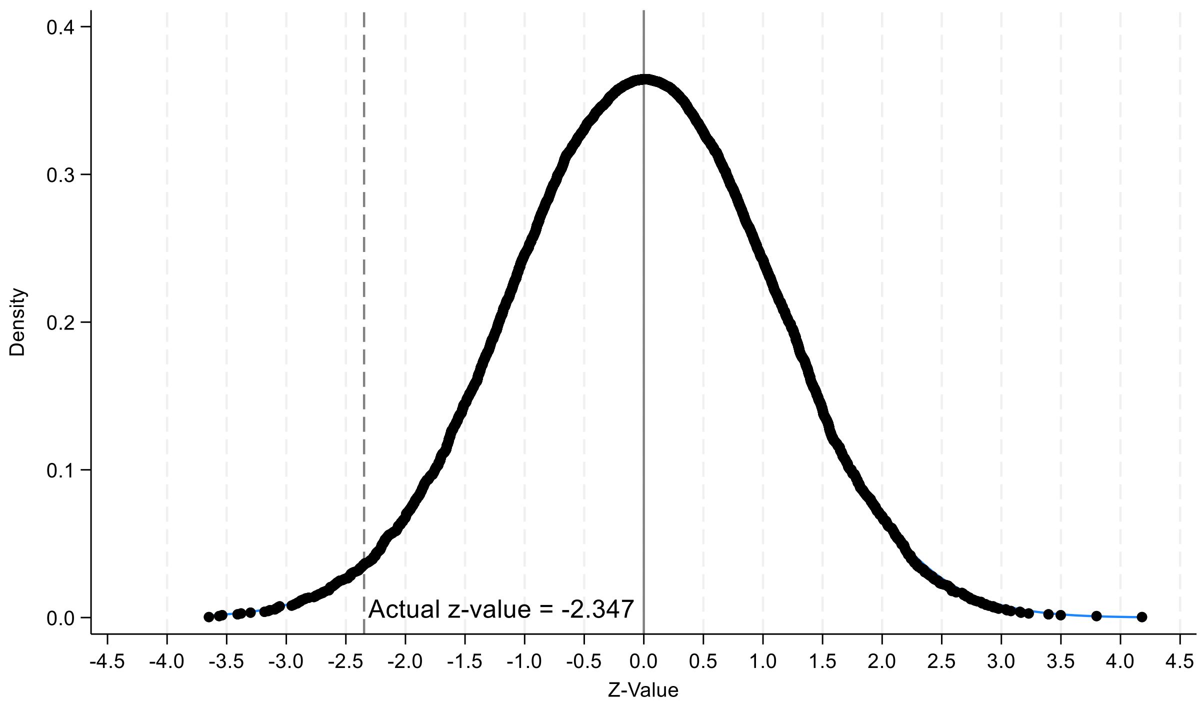

Table 1. Summary statistics

This table presents summary statistics of the main variables. Our sample period runs from 2014 through 2020. All variables are at an annual frequency. The variable definitions are provided in the Appendix.

Variables	Number	Mean	Standard Deviation	Minimum	Median	Maximum
Misconduct	16494	0.166	0.372	0	0	1
Question number	16494	4.186	1.355	0	4.317	8.622
Reply number	16494	3.988	1.563	0	4.220	8.622
Reply ratio	16174	0.882	0.248	0	1	1
Reply interval	15531	2.036	1.093	0	1.764	6.963
Reply length	15626	4.207	0.469	1.099	4.211	6.151
Question sentiment	16174	0.398	0.122	0	0.398	1
Reply sentiment	15626	0.686	0.156	0	0.694	1
Firm age	16494	18.253	5.513	4	18	52
Firm size	16494	22.268	1.266	19.722	22.111	25.950
Financial leverage	16494	0.427	0.203	0.056	0.417	0.898
Growth rate	16494	0.175	0.430	-0.587	0.101	2.602
Tobin's Q	16494	2.174	1.947	0.168	1.585	9.988
Stated-owned enterprise	16494	0.319	0.466	0	0	1
Ownership concentration	16494	0.529	0.149	0.197	0.530	0.877
Institutional shareholding ratio	16494	0.389	0.232	0	0.396	0.870
Independent director	16494	0.376	0.054	0.286	0.364	0.571
Board size	16494	2.118	0.199	1.609	2.197	2.708
Number of board meetings	16494	2.348	0.352	1.609	2.303	3.219
CEO duality	16494	0.281	0.449	0	0	1
Audit quality	16494	0.055	0.228	0	0	1
Stock turnover	16494	6.023	4.829	0.546	4.603	24.130
Stock return	16494	0.129	0.564	-0.702	-0.002	3.103
Stock volatility	16494	0.030	0.010	0.013	0.028	0.057

Table 2. Baseline regressions

This table reports the estimated relations between the investor-initiated interactions and corporate misconduct based on a probit model. The dependent variable *Misconduct* is an indicator variable equal to one if a firm commits misconduct and zero otherwise. The independent variables of our interest are *Question number* and *Reply number* that capture the interactions between investors and firms on the interactive platforms. *Question number* is the natural logarithm of one plus the total number of questions asked by investors for each firm. *Reply number* is the natural logarithm of one plus the number of replies made by a firm. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1)	(2)
Question number	-0.050***	
	(-3.693)	
Reply number		-0.054***
		(-4.645)
Firm age	0.005	0.005
	(1.328)	(1.227)
Firm size	-0.017	-0.018
	(-0.729)	(-0.762)
Financial leverage	0.845***	0.834***
	(7.646)	(7.557)
Growth rate	-0.012	-0.011
	(-0.398)	(-0.347)
Tobin's Q	-0.018	-0.019
	(-1.453)	(-1.516)
Stated-owned enterprise	-0.431***	-0.436***
	(-9.068)	(-9.167)
Ownership concentration	-0.704***	-0.697***
	(-5.218)	(-5.218)
Institutional shareholding ratio	-0.373***	-0.379***
	(-3.667)	(-3.726)
Independent director	0.403	0.393
	(1.035)	(1.009)
Board size	0.011	0.010
	(0.087)	(0.087)
Number of board meetings	0.236***	0.238***
	(4.850)	(4.885)
CEO duality	-0.002	-0.002
	(-0.045)	(-0.058)
Audit quality	-0.224**	-0.230**
	(-2.160)	(-2.233)
Stock turnover	-0.023***	-0.023***
	(-5.482)	(-5.461)
Stock return	-0.081**	-0.079**
	(-2.448)	(-2.405)
Stock volatility	23.857***	23.848***
	(7.912)	(7.922)
Constant	-1.191**	-1.160*
	(-1.972)	(-1.924)
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R^2	0.0808	0.0818
Number	16494	16494

Table 3. Difference-in-differences approach

This table examines the relation between investor-initiated interactions and corporate misconduct based on a probit difference-in-differences (DiD) regression around the adoption of an online interactive platform for the Shenzhen Stock Exchange and prior to the adoption of an online interactive platform by the Shanghai Stock Exchange. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. The treatment group consists of firms listed in the Shenzhen Stock Exchange in 2009, one year prior to the launch of *Easy Interaction* by the Shenzhen Stock Exchange in January 2010. The control group consists of firms listed in the Shanghai Stock Exchange in 2009. We match each treated firm to a control firm using a one-to-one nearest-neighbor propensity score matching (PSM) approach. The variable *Post* is equal to one for years 2010, 2011, and 2012, and zero for years 2008 and 2009. All control variables are lagged by one year and defined as in the Appendix. The results including and excluding the interaction terms between the control variables and the post dummy are reported in columns (1) and (2), respectively. The *z*-statistics, based on firm-clustered standard errors, are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) (2008-2012)	(2) (2008-2012)
Treat × Post	-0.293**	-0.264**
	(-2.347)	(-2.123)
Treat	0.195	0.177
	(1.602)	(1.441)
Constant	0.686	0.646
	(0.338)	(0.430)
Controls	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Controls*Post	Yes	No
Pseudo R^2	0.115	0.108
Number	2981	2981

Table 4. Parallel Trend Analysis

This table reports the test results for parallel trend analysis between 2008 and 2012. The dependent variable *Misconduct* is an indicator variable equal to one if a firm commits misconduct and zero otherwise. The treatment group consists of firms listed in Shenzhen Stock Exchange in 2009, one year prior to the launch of its online interactive platform in January 2010. The control group consists of firms listed in Shanghai Stock Exchange in 2009. The treated firm is matched to a control firm using a one-to-one nearest-neighbor PSM approach. $Before^{-2}$ is equal to two years prior to the launch of *Easy Interaction* in January 2010 and zero otherwise. $Current^{0}$ is equal to one in the year (2010) when *Easy Interaction* was launched. $After^{1}$ and $After^{2}$ are equal to one for the first (2011) and second (2012) years after the launch of *Easy Interaction*. All control variables are lagged by one year and defined as in the Appendix. The *z*-statistics, based on firm-clustered standard errors, are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Reference year = 2009	(2) Reference year = 2009
$Treat \times Before^{-2}$	0.181	0.159
	(1.304)	(1.135)
$Treat \times Current^{0}$	0.030	0.037
	(0.211)	(0.261)
$Treat \times After^{1}$	-0.063	-0.037
	(-0.476)	(-0.290)
$Treat \times After^{2}$	-0.337**	-0.293*
	(-2.088)	(-1.839)
Treat	-0.447**	-0.415**
	(-2.570)	(-2.378)
Constant	0.679	0.670
	(0.334)	(0.444)
Controls	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Controls*Post	Yes	No
Pseudo R^2	0.117	0.109
Number	2981	2981

Table 5. Placebo test

This table presents the DiD results for an assumed pseudo-shock in 2009. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. The treatment group consists of firms listed in the Shenzhen Stock Exchange in 2009, one year before its online interactive platform was launched in January 2010. The control group consists of firms listed in the Shanghai Stock Exchange in 2009. The Shanghai Stock Exchange instituted its online interactive platform in 2013. Each treated firm is matched with a control firm using a one-to-one nearest-neighbor PSM approach. Columns (1) and (2) assume that *Easy Interaction* was launched in 2009 when including and excluding the interaction terms between all the control variables and the indicator variable *Post*. The estimation period is 2007 to 2011 for the pseudo-shock assumed to occur in 2009. All control variables are lagged by one year and defined as in the Appendix. The *z*-statistics, based on robust standard errors clustered at the firm level, are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) (2007-2011)	(2) (2007-2011)
Treat × Post	-0.211	-0.194
	(-1.505)	(-1.414)
Treat	0.439***	0.425***
	(3.286)	(3.184)
Constant	2.775	2.449
	(1.194)	(1.528)
Controls	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Controls*Post	Yes	No
Pseudo R^2	0.142	0.137
Number	2928	2928

Table 6. Alternative measures of the replies of listed companies

This table reports the results of probit regressions of corporate misconduct on the alternative measures of replies. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. *Reply ratio* is the ratio of the number of questions replied to divided by the number of total questions asked. *Reply interval* is the natural logarithm of one plus the average number of days between a question being asked and replied to in a year. *Reply length* is defined as the natural logarithm of one plus the average number of words per reply by a firm in a year. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1)	(2)	(3)
Reply ratio	-0.374***		
	(-5.875)		
Reply interval		0.055***	
		(3.558)	
Reply length			-0.072**
			(-1.992)
Constant	-0.531	-1.012*	-0.777
	(-0.876)	(-1.649)	(-1.250)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Pseudo R^2	0.0832	0.0806	0.0794
Number	16174	15531	15626

Table 7. The sentiment measure of investor-initiated interactions

This table reports the estimated relations between the sentiment measure of investor-initiated interactions and committed misconduct based on a probit model. The dependent variable *Misconduct* equals one if a firm commits a misconduct and zero otherwise. The main explanatory variables of our interest are *Question sentiment* and *Reply sentiment*, which are calculated by using the Python library of sentiment analysis for simplified Chinese with respect to SnowNLP. Columns (1) – (3) and Columns (4) – (6) are the negative, neutral, and positive subsamples based on the industry tercile for questions asked and replies made. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1) Negative sentiment subsample	(2) Neutral sentiment subsample	(3) Positive sentiment subsample	(4) Negative sentiment subsample	(5) Neutral sentiment subsample	(6) Positive sentiment subsample
Question sentiment	-0.689**	-0.879	0.832***			
	(-2.169)	(-1.260)	(2.866)			
Reply sentiment				-0.679***	0.694	-0.181
				(-2.916)	(1.321)	(-0.467)
Constant	-1.030	-0.295	-1.986**	-1.520*	-0.460	-1.338
	(-1.213)	(-0.325)	(-2.051)	(-1.670)	(-0.470)	(-1.314)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0959	0.102	0.0927	0.103	0.106	0.0852
Number	5486	5388	5284	5301	5201	5100

Table 8. Information asymmetry channel

Panels A and B report the estimated relations between investor-initiated online communications proxied by questions asked (replies made) and the incidence of corporate misconduct using a probit model. Information asymmetry is measured as the dispersion in analyst earnings forecasts or stock price synchronicity. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

Panel A. Dispersion in analyst earnings forecasts as a proxy for information asymmetry

Dispersion in analyst earnings forecasts is calculated as the absolute difference between the mean of forecasted earnings per share and actual earnings per share scaled by the stock price at the beginning of the year. The two subsamples are delineated based on the industry median of the dispersion in analyst earnings forecasts.

	(1) Low dispersion in analyst earnings forecast *Misconduct*	(2) High dispersion in analyst earnings forecast *Misconduct*	(3) Low dispersion in analyst earnings forecast *Misconduct*	(4) High dispersion in analyst earnings forecast *Misconduct*
Question number	-0.005	-0.070***		
	(-0.223)	(-3.440)		
Reply number			-0.020	-0.062***
			(-1.065)	(-3.536)
Constant	-1.227	-2.099**	-1.203	-2.006**
	(-1.341)	(-2.284)	(-1.314)	(-2.193)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value of χ^2	0.0139		0.0637	
Adjust R^2	0.0957	0.106	0.0960	0.106
Number	5870	5716	5870	5716

Panel B. Stock price synchronicity as the proxy for information asymmetry

Stock price synchronicity is the logarithm transformation of the adjusted R^2 obtained by regressing a firm's stock return on market and industry benchmarks. The two subsamples are delineated based on the industry median of stock price synchronicity.

	(1) Low stock price synchronicity *Misconduct*	(2) High stock price synchronicity *Misconduct*	(3) Low stock price synchronicity *Misconduct*	(4) High stock price synchronicity *Misconduct*
Question number	0.006	-0.050***		
	(0.334)	(-2.812)		
Reply number			-0.014	-0.055***
			(-0.900)	(-3.669)
Constant	-0.909	-0.927	-0.969	-0.896
	(-1.149)	(-1.184)	(-1.227)	(-1.146)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value of χ^2	0.0139		0.0364	
Adjust R^2	0.0967	0.0822	0.0969	0.0833
Number	7832	8001	7832	8001

Table 9. Internal control quality

This table reports the estimated relation between questions asked (replies made) and the incidence of corporate misconduct using a probit model. The subsamples of good and bad internal controls are classified based on the industry median of firm internal controls. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1) Good internal control	(2) Bad internal control	(3) Good internal control	(4) Bad internal control
Question number	-0.070***	-0.052***		
	(-3.550)	(-3.284)		
Reply number			-0.067***	-0.056***
			(-4.001)	(-4.115)
Constant	-0.469	-2.293***	-0.381	-2.279***
	(-0.567)	(-3.174)	(-0.462)	(-3.157)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value of χ^2	0.4285		0.5637	
Pseudo R^2	0.0887	0.0808	0.0895	0.0818
Number	8203	8219	8203	8219

Table 10. Print media coverage

This table reports the estimated relations between questions asked (replies made) and the incidence of corporate misconduct using a probit model. Media coverage is measured as the natural logarithm of total number of newspaper headlines about a firm. The subsamples of high and low media coverage are classified based on the industry median of firm media coverage. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1) High media	(2) Low media	(3) High media	(4) Low media
Question number	-0.064***	-0.044**		
	(-3.499)	(-2.462)		
Reply number			-0.068***	-0.046***
			(-4.350)	(-3.044)
Constant	-0.895	-1.548*	-0.856	-1.522*
	(-1.124)	(-1.827)	(-1.076)	(-1.797)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value of χ^2	0.3902		0.2885	
Pseudo R^2	0.1073	0.0769	0.1089	0.0775
Number	7365	9124	7365	9124

Table 11. Internet searching

This table reports the estimated relations between questions asked (replies made) and the incidence of corporate misconduct using a probit model. The subsamples of high and low internet searching are classified based on the industry median of firm internet searching. The dependent variable *Misconduct* equals one if a firm commits misconduct and zero otherwise. All explanatory variables are lagged by one year and defined as in the Appendix. The *z*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1) High Searching	(2) Low searching	(3) High Searching	(4) Low searching
Question number	-0.063***	-0.050**		
	(-3.598)	(-2.347)		
Reply number			-0.061***	-0.056***
			(-4.151)	(-3.105)
Constant	-0.118	-0.979	-0.063	-0.984
	(-0.148)	(-1.053)	(-0.079)	(-1.059)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
P-value of χ^2	0.5971		0.8214	
Pseudo R^2	0.0882	0.102	0.0893	0.103
Number	7355	7355	7355	7355

Table 12. Investor-initiated communications and firm value

This table reports the OLS regression of firm value, as measured by Tobin's Q, on investor-initiated interactions, questions asked by investors or replies made by firms. The dependent variable in columns (1) – (2) is Tobin's Q in the current year, and the dependent variable in columns (3) – (4) is Tobin's Q in the following year. Tobin's Q is measured as the market value of assets divided by the book value of assets. All explanatory variables are in current year and defined as in the Appendix. The *t*-statistics are displayed in the parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard errors are clustered at the firm level to allow for serial correlation. The sample spans from 2014 to 2020.

	(1) Contemporaneous Tobin's Q	(2) Contemporaneous Tobin's Q	(3) Lead Tobin's Q	(4) Lead Tobin's Q
Question number	0.060***		0.034***	
	(4.645)		(4.323)	
Reply number		0.029***		0.020***
		(2.632)		(2.967)
Tobin's Q			0.664***	0.665***
			(43.742)	(44.073)
Constant	14.654***	14.586***	4.404***	4.351***
	(21.044)	(20.927)	(11.574)	(11.505)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.466	0.465	0.610	0.610
Number	16494	16494	12824	12824