Journal of Accounting and Economics 74 (2022) 101524

Contents lists available at ScienceDirect

Journal of Accounting and Economics

journal homepage: www.journals.elsevier.com/journal-of-accounting-and-economics

Shall we talk? The role of interactive investor platforms in corporate communication☆

Charles M.C. Lee [a, b], Qinlin Zhong [c, *]

[a] Graduate School of Business, Stanford University, United States
[b] Foster School of Business, University of Washington, United States
[c] School of Management, Fudan University, China

A R T I C L E   I N F O

Article history:
Received 29 April 2021
Received in revised form 7 March 2022
Accepted 21 July 2022
Available online 3 August 2022

JEL classification Codes
M41
M45
G14
G15
G39

Keywords
Corporate disclosure
Investor relations
Information processing costs
Interactive communication
Market liquidity
Price informativeness

A B S T R A C T

Between 2010 and 2017, Chinese investors used an investor interactive platform (IIP) to ask public companies around 2.5 million questions, the vast majority of which received a reply within two weeks. We analyze these IIP dialogues using a BERT-based algorithm and provide preliminary evidence on their causes and consequences. Our analyses show most questions reflect investors' difficulties in processing information already in the public domain. Controlling for other news, higher IIP activity is associated with increases in trading volume, return volatility, market liquidity, and price informativeness as well as decreases in bid-ask spread. Financial statement-related postings increase around the adoption of new accounting standards. Collectively, our results show that investors face significant information processing costs but that IIP activities help reduce these costs, leading to improvements in stock price formation.

1. Introduction

Clear communication is generally achieved through ongoing dialogue between parties. In contrast, most corporate disclosure settings studied by academics emphasize supply-side issues. In these settings, managerial priorities dictate the timing and content of corporate communiqués, with little or no direct input from investors. As a result, while an extensive literature has developed around managerial incentives for corporate disclosure, relatively little is known about the demand-side — i.e., what investors want to know on a day-to-day basis, what problems they encounter as they process corporate

☆ We thank John Core (editor), Elizabeth Blankespoor (discussant), an anonymous referee, Patricia Dechow, Ed deHaan, Suzie Noh, Richard Sloan, Marcus Kirk (HARC Discussant), Jedson Pinto (FARS Discussant), and seminar participants at the 2021 JAE Conference, the USTC-UW Conference, USC, Indiana University, Hong Kong Poly University, the HARC conference, the AAA Spark Meeting (Best Paper by the Western Region), and the FARS conference for helpful suggestions and comments. We are grateful to the Stanford GSB Research Fellows Program for financial support and to Jialu Sun for excellent research assistance. Qinlin Zhong appreciates financial support from the National Natural Science Foundation of China (No. 71902183).

* Corresponding author.
E-mail addresses: clee8@stanford.edu (C.M.C. Lee), zhongqinlin@fudan.edu.cn (Q. Zhong).

https://doi.org/10.1016/j.jacceco.2022.101524
0165-4101/

news, how these problems affect their trading, and ultimately how these information processing costs may impact the formation of market prices.

In this study, we examine the causes and consequences of a new form of *interactive* corporate communication. Since January 2010, most public firms in China have participated on an interactive communication platform, wherein questions raised by the investing public are answered by corporate management. Launched by two major stock exchanges, these investor interactive platforms (IIPs) were quickly embraced by both investors and corporations. Between 2010 and 2017, Chinese investors posted around 2.5 million questions on these platforms. The vast majority of these questions received a formal reply from company management, typically within a few days or weeks. By the end of 2017, over 99% of all Chinese listed companies were interacting with their investors on the platforms. Using website-extraction techniques, we collect a full set of dialogues from these platforms for January 2010 to December 2017, with a view toward better understanding this phenomenon.

We view these IIPs as a significant development in corporate communications for three reasons. First, because the postings are driven by users of financial information rather than corporations, *the nature and content of the questions raised by investors* can provide important new insights into the daily information needs of ordinary investors.[1] Second, 12 years after their introduction, the IIPs are an integral part of the corporate communications landscape in China. Given their unique attributes (summarized in Section 2.3) and widespread adoption, *it is important to understand how IIP activities affect investor trading*. Finally, to the extent that IIPs help reduce investor information costs, theory suggests firms participating in IIPs could see improvements in their price formation. Therefore we investigate *how engagement on IIPs relates to a firm's market liquidity and price informativeness.* (We use the term “price informativeness” here to denote the extent to which current prices capture information about future earnings.) Our subsequent analyses are organized around the attainment of these three research goals.

With respect to the first goal, we aim to understand the types of problems investors encounter when using public information. Recent findings on the costs of investor information processing (e.g., Blankespoor et al. (2019; BDWZ) and Blankespoor et al. (2020; BDM)) suggest investors often need help understanding and acting on financial information in the public domain. In many respects, these Chinese IIPs are an excellent setting in which to study investors’ information processing costs. Because participating firms are not allowed to use the IIPs to disseminate *new* information, most questions raised by investors involve problems encountered while trying to understand and act on previously disclosed information.

To analyze these questions, we first manually categorize a random subset of investor postings (2% of total) and use this as training data. We then leverage BERT, a state-of-the-art AI approach to natural language processing, to categorize the remaining postings as to their *nature* and *content*. Our results show that the vast majority of postings are seeking answers to or explanations of specific items (79.8%), followed by suggestions or other comments to management (16.6%) and requests to verify/deny rumors or correct misunderstandings (2.85%). In terms of the specific content of questions, the 10 topics investor most frequently ask about, in descending order, are products or business operations (21.7%), financial reports (18.6%), corporate governance (9.0%), stock trading (7.1%), asset restructuring (6.6%), investments (5.9%), financing (4.8%), dividends (4.4%), industry-related questions (4.4%), and insider trading (4.1%).

Overall, consistent with BDWZ and BDM, our evidence suggests that investors face a wide range of problems when trying to understand and act on public information. Most investors who post questions want help in understanding company operations or interpreting corporate financial data. Sometimes their questions relate to facts that could have been found with a more diligent search; other times investors misunderstand accounting conventions and do not know how company reports will reflect economic events. Investors frequently ask companies to address market rumors or discuss the effect of macro conditions on the business. And finally, sometimes they simply want to vent or to tell management how to handle various situations (See Appendix A for examples.).

In the second stage of our analyses, we examine the effect of IIP activities on investor trading. Specifically, we use a short-window research design to document the abnormal trading volume and absolute abnormal return associated with daily variations in the level of IIP activities (including the number of questions and replies posted as well as the length of these questions and replies). To distinguish IIP activities from other firm-related disclosures, we control for five other types of news releases: earnings announcements, reports of material events, managerial earnings forecasts, sell-side analyst reports, and firm mentions in the news media.

We find that, while the five traditional types of firm-related disclosures have a positive association with IIP activities, their collective ability to explain variations in daily IIP activity is limited. Statistically, investors are more likely to ask questions and firms are more likely to reply on days with an information event. This result holds for each of the five events cited above. However, taken together, these five events explain less than one percent of the variation in the daily fluctuation in IIP activities. In short, most of the variation in IIP postings is not attributable to the information events commonly studied in the literature.

Although IIPs cannot be used for the release of new information, the dialogue between managers and investors happening on the platforms can nevertheless stimulate trading by facilitating information processing by investors. We examine this

[1] We have no reason to believe the questioners are not “ordinary” or that they are particularly sophisticated. We similarly do not believe the postings undergo significant vetting or filtering. Out of curiosity, we posted a few questions, and, in each case, the question appeared as we asked it, and the company replied reasonably quickly.

proposition by regressing two proxies for daily trading (abnormal volume and abnormal return volatility) on measures of daily IIP activity, controlling for known information events and other potential drivers of abnormal trading.

Our results show a strong positive association at the daily level between abnormal trading volume and different measures of daily IIP activity. We find similar results when the dependent variable is absolute abnormal return. Overall, these findings show that, controlling for other corporate information events, higher levels of IIP activities are associated with a stronger market reaction. While these findings are consistent with IIP activities informing investors, higher IIP activities also may simply attract investor attention, leading to noise trading (e.g., Barber and Odean, 2008). We try to disentangle these possibilities through a third set of tests on price formation.

Theory indicates that, when information processing costs are nontrivial, improved disclosure that reduces these costs can (a) increase market liquidity (Amihud and Mendelson, 1986; Diamond and Verrecchia, 1991; Leuz and Verrecchia, 2000), (b) reduce investor integration costs (Barry and Brown, 1985 and BDM, 2020), (c) expand a firm's investor base (Merton, 1987), or (d) a combination of these, leading to lower costs of capital and improved market depth. Our first set of tests showed that investors encounter many integration problems while attempting to act on public information. Our second set of tests found that higher daily IIP activities lead to higher trading volume and return volatility, possibly because these activities help mitigate investor concerns. In this last set of tests, we directly evaluate the extent to which IIP activities are associated with measurable benefits to the firms themselves.

We first examine the effect of IIP activity on daily bid-ask spreads, a common proxy for information asymmetry costs. We find the average bid-ask spread is lower on days with higher IIP activities. At first blush, it may seem surprising that demand-side platform activities (the posting of new questions) per se can also improve market liquidity. However, as discussed in Sec 2.3, investors who sign up to follow a firm can receive real-time IIP updates/alerts via their personal IIP account (mobile app or on a computer) about any new questions and replies. It is therefore not entirely surprising that new IIP questions can increase investor attention and possibly stimulate greater liquidity provision. Overall, the evidence suggests increased daily IIP activities are associated with higher market liquidity, potentially due to lower information asymmetry risk.

We also conduct a second market liquidity test based on the Amihud (2002) illiquidity measure. Our results show a significantly lower Amihud ratio on days with higher IIP activities, indicating that greater engagement on the platform is associated with a reduction in the price impact of a given volume of trade. As with the bid-ask spread test, this result suggests that higher daily IIP activity is associated with an increase in market liquidity.

As a further robustness check, we conduct two longer-window tests using quarterly data and control variables more commonly seen in longer-window analyses. First, we examine the effect of quarterly IIP activity on the average quarterly bid-ask spread and Amihud illiquidity ratio, after controlling for the frequency of other firm-related disclosures over each firm-quarter. Our results confirm that, at the quarterly level, a higher degree of interactive communication is associated with smaller bid-ask spreads and lower Amihud illiquidity ratios. Second, we exploit the staggered implementation of IIPs across the two Chinese exchanges to conduct a difference-in-difference analysis of the effect of IIP activities on market liquidity. These results again show that active IIP firms experience significantly greater improvement in market liquidity over the treatment period than their propensity-score-matched control firms.

When liquidity improves, information can be more readily incorporated into price, thus increasing the informativeness of price with respect to future earnings (Kerr et al., 2020). To examine the relation between IIP and firms' price informativeness, we conduct a quarterly future earnings response coefficient, or FERC, test (see, for example, Lee and Watts, 2021; Drake et al., 2012; Fernandes and Ferreira, 2009). Specifically, we examine the ability of quarterly returns (cumulative abnormal returns measured over days t-60 to t-1, relative to each quarter t's earnings announcement date) to predict that period's standardized unexpected earnings (quarter t *SUE*). Our results show that the cumulative pre-earnings announcement return is more positively correlated with future standardized unexpected earnings when investors and managers post more often on the interactive platform. These findings are consistent with IIP activities reducing investor information processing costs and thus accelerating the speed of price discovery associated with future earnings.

As a final test, we examine changes in IIP activities associated with the mandatory adoption of new accounting standards. Mandatory adoptions of new standards are, for the most part, non-information events that do not change the economics of the business. However, investor integration costs are likely higher in the period immediately following adoption due to increased accounting complexity. In July 2014, the Accounting Standards Board of China formally revised five accounting standards and adopted three new ones. We examine changes in IIP activities, particularly financial statement-related questions and responses, in the quarter immediately following this change.

Our results show that, in the following quarter, the number of financial statement-related questions (+13%) and replies (+10%) significantly increased. During this quarter, the *proportion* of total questions (replies) that addressed financial reporting topics increased by 3.5% (3.1%). These findings indicate that changes in accounting standards can increase investor information processing costs, leading to more financial statement-related questions. To our knowledge, this is the first direct evidence that the adoption of new accounting standards can increase investor confusion over firms' financial reports. These results also support the view that IIPs can help with information integration.

Taken together, our findings highlight the importance of investor information processing costs. Research has focused largely on investor information awareness and acquisition costs. Our results show that, on a day-to-day basis, investors are concerned with a wide range of integration problems associated with public information. Perhaps more importantly, we show that increased IIP activities are associated with improvements in firms' market liquidity and price informativeness, further supporting the view that IIPs can mitigate investor information processing costs.

The remainder of this paper is organized as follows. Section 2 discusses our research motivation and provides further institutional background on these IIPs. Section 3 presents statistics on IIP adoption and usage, case studies, and a systematic analysis of investor postings. Section 4 presents our main results on investor trading and market price formation. Section 5 concludes.

2. Motivation and institutional background

2.1. Investor information needs

Our first goal is to better understand the demand-side of corporate communications. Specifically, we wish to illuminate the informational issues investors face as they consider investing in a company. Recent findings suggest investors do incur significant costs when processing information that is already public (BDWZ, 2019; BDM, 2020). The BDWZ and BDM framework of information usage entails three sequential steps: awareness, acquisition, and integration. According to BDWZ, awareness refers to someone becoming aware that a disclosure exists; acquisition refers to costs associated with acquiring the disclosure or specific information within the disclosure; integration refers to costs associated with combining and integrating that information into a trading decision, including the cost of learning accounting and financial statement analysis.[2] A key motivation for this study is to assess the importance of information processing costs to investors and provide empirical evidence on the nature of their day-to-day needs.

Research suggests such costs may be substantial. Many unsophisticated investors find financial disclosures difficult to read (Jones and Shoemaker, 1994). Retail investors are more likely to be affected by form versus substance issues, due to limited processing capabilities and a lack of expertise (Maines and McDaniel, 2000). Miller (2010) finds that reporting complexity also impedes small investors' processing and understanding of information. Conversely, Lawrence (2013) shows that concise and plainly written financial disclosures facilitate understanding of reported numbers. Cyber news delivery may lead to information overload, which exacerbates the problem. As overloaded individuals resort to heuristics, information assimilation by the market may be hampered (Chapman et al., 2019). Rumors and falsehoods, spread through blogs and investor forums, can further complicate investor decision-making and hinder price formation (Drake et al., 2017).

In short, prior work suggests that investors, particularly retail investors, likely face significant costs when attempting to integrate publicly available information into their trading decisions. At the same time, these studies recognize it is difficult for researchers to gain insights into the exact nature of investors' informational difficulties. An important goal of this study is to provide new large-sample evidence on the nature and extent of the problems investors experience when using public information to evaluate listed firms.

2.2. Causes and consequences of IIP activity

Another goal of this study is to better understand the economic causes and consequences of dialogue between corporations and their shareholders. While an exhaustive analysis of the *causes* (or economic determinants) of IIP activity is beyond the scope of this study, we document how these activities relate to five other information events from the literature: earnings announcements, reports of material events, managerial earnings forecasts, sell-side analyst reports, and firm mentions in the news media. Specifically, our goal is to better understand (a) how IIP engagement fits into each firm's broader communication strategy and (b) how much of the activities on these IIPs are triggered by and can be attributed to these other information events.

With respect to the economic consequences of IIP activities, our goal is again modest. We do not study all the possible consequences of IIP activity. We also do not conduct detailed tests on the market reaction to each of the many different types of questions raised by investors on these IIPs. Our aim is to lay down a foundation for more detailed studies on the information content of these postings. With this in mind, we are focusing sharply on understanding two important issues: (a) whether more active participation on these platforms is associated an increase in investor trading (proxied by abnormal trading volume and return volatility), after controlling for other news events, and (b) whether IIP activities are associated with measurable benefits to firms' price formation (in particular, market liquidity and price informativeness).

2.3. Interactive platforms

According to the IIP websites, China's two major stock exchanges, SZSE and SHSE, each launched its platform with the intent "to establish a direct bridge of communication between investors and listed firms." The SZSE platform, called Hu Dong

[2] Using the Associated Press's staggered rollout of nationally distributed "robo-journalism" articles of firms' earnings announcements, BDWZ disentangle *awareness* and *acquisition* costs from other frictions and find that these two types of costs are not the primary barriers to individual investors' use of accounting information in trading decisions. Their results instead point to *integration* costs (frictions associated with understanding and acting on information) as a significant impediment to investor information processing. In a similar spirit, BDM observe that "[t]he existence of disclosure processing costs means that disclosures are not 'public' information as traditionally defined, but instead can be a form of costly private information."

Yi (互动易), was launched on January 1, 2010; the SHSE platform, dubbed e Hu Dong (e互动), was launched 3.5 years later, on July 5, 2013.

Each listed firm has its own community on its platform. Investors can directly post their questions on the target firm's community page. Participating firms must appoint a high-level employee (a "board secretary") to oversee the replies made on its behalf. While the platform's operations are supervised by the stock exchanges, each listed firm is legally responsible for its own replies. A *digital identity certification system* ensures all answers are in fact provided by the target firm. A similar system allows the sponsoring exchange to trace the identity of the questioner as needed.

The questions are submitted to the exchange, not to the firm. Once a user submits a question, the stock exchange is in control of the process and participating firms have no right to edit or delete questions. Each exchange performs a cursory review of the question before releasing it, but we are not aware of any instance where an exchange significantly altered a question. The firm and the public then see the question simultaneously when the exchange releases it. Although the identity of an IIP participant is not known to other participants (and firms), the sponsoring exchange has this information, and can quickly trace the identity of any IIP user (or firm representative) in the event of any problems or concerns. This monitoring mechanism ensures some accountability in terms of what each side posts.[3]

The IIP platform also facilitates the transmission of IIP activities to investors in real time. An investor who submits a question can receive notification via a cellphone text when her/his question is publicly posted by the exchange and when an answer is received from the firm. In addition, any investor who follows a given firm can sign up to receive an alert/update via his/her personal IIP account (in mobile app or on a computer) whenever that firm receives a new question or posts a new reply.

Company participation on these IIPs is best described as quasi-mandatory. The stock exchanges do not explicitly sanction firms that fail to respond to posted questions. However, each exchange monitors firm participation and will grant "honors and awards" (bragging rights) to firms that perform best on various investor-friendliness metrics. Importantly, Chinese security laws prohibit the use of these platforms to disseminate significant new information.[4] As a result, the type of information that can be disclosed on these platforms is, by design, already public. From our perspective, this is helpful, as the dialogues recorded on these platforms should provide a direct chronology of the types of problems investors encounter when processing public information.

To summarize, these IIPs are a novel development in corporate communications that is distinct from other disclosure venues in important ways. First, *their officially sanctioned status* distinguishes them from social media posts, chat rooms, and investment blogs, which routinely carry unverified content of dubious quality. Second, unlike other forms of corporate disclosure (e.g., 10Ks, 8Ks, press releases, or even corporate tweets), *IIPs are investor-initiated*, as investors dictate the topics discussed. Third, *most questions are raised by ordinary investors* (as distinct from the Q&A sessions after corporate conference calls).[5] Fourth, *these IIPs do not disclose new information* and are dedicated to explaining prior disclosures. For these reasons, we believe the activities on these platforms can provide unique insights into the information processing problems faced by investors.

3. Data and descriptive statistics

Our initial sample consists of all nonfinancial A-share firms listed on China's two stock exchanges during the period 2010 to 2017. Our sample begins in January 2010, the month that the Shenzhen Stock Exchange (SZSE) launched its interactive platform, called Hu Dong Yi. Using the platform data, we first identify all firms present on the platform. For each, we extract the entire date-stamped history of questions and responses directly from the firm's community webpage.

3.1. Adoption and usage

Table 1 summarizes corporate adoption of interactive platforms by year for the SZSE, SHSE, and both stock exchanges combined. In the first year of the launch of Hu Dong Yi, 76.51% of the firms listed on SZSE joined the platform. By the second year, 95.1% of the SZSE firms became active. For e Hu Dong, more than 90% of the firms on the SHSE joined the platform in 2013, the year of its launch. By the end of 2017, corporate adoption rate for these IIPs has reached 99% across the two

[3] As compared to the U.S. and Europe, in China people are less likely to hide from the government (e.g., Wu et al., 2011). The government knows each person's cell phone number and can easily link the cell number to a person's ID and other information (BBC, 2019). The government provides cell numbers and ID links to the exchange as needed. This institutional feature of Chinese society greatly increases the likelihood of discovery in the event of overt misbehavior on the platform, and we think it is an important deterrent against such misbehavior.

[4] For example, the SHSE has the following regulatory notice on its IIP (the SZSE platform has a similar notice): "For disclosed matters, the listed firm can provide full and detailed answers or explanations. For undisclosed matters, the listed firms should inform investors to pay attention to formal announcements. The interactive communication cannot serve as an alternative way to disclose information and undisclosed material information cannot be communicated on the interactive platform."

[5] The closest other forms of corporate communication are the Q&A segments of corporate conference calls (Matsumoto et al., 2011) and, more recently, site visits to Shenzhen-listed companies (Bowen et al., 2018; Cheng et al., 2019; So et al., 2020). However, unlike IIPs, conference calls and site visits occur only a few times a year, and participants in these activities are professional analysts and asset managers rather than retail investors.

Table 1
Corporate adoption of investor interactive platforms (IIPs).

year	SZ Stock Exchange			SH Stock Exchange			Total		
	Participant	N of firm	Percent	Participant	N of firm	Percent	Participant	N of firm	Percent
2010	915	1,196	76.51%	0	852	0.00%	915	2,048	44.68%
2011	1,329	1,398	95.06%	0	880	0.00%	1329	2,278	58.34%
2012	1,493	1,503	99.33%	0	901	0.00%	1493	2,404	62.10%
2013	1,494	1,542	96.89%	817	907	90.08%	2311	2,449	94.37%
2014	1,573	1,603	98.13%	920	962	95.63%	2493	2,565	97.19%
2015	1,706	1,722	99.07%	1,011	1,031	98.06%	2717	2,753	98.69%
2016	1,830	1,874	97.65%	1,103	1,161	95.00%	2933	3,035	96.64%
2017	2,049	2,062	99.37%	1,324	1,345	98.44%	3373	3,407	99.00%

This table reports corporate adoption of investor interactive platforms by year and exchange. Participating firms belong to either the Shenzhen (SZ) or Shanghai (SH) Stock Exchange. The sample includes all nonfinancial A-share firms listed on both exchanges, between 1/2010 and 12/2017, inclusively. A firm is deemed to have participated on the platform if there is at least one investor inquiry during the year.

exchanges (See Fig. 1 for a graphical depiction.). Clearly companies and investors quickly embraced these IIPs, and they are now an integral part of investor communications.

Table 2 reports the level of investor and corporate participation by quarter. Column 1 reports the average number of questions posted on each firm's website. Column 2 reports the average number of responses from management. Column 3 reports the response rate, calculated as the number of responses divided by the number of questions for each firm. Column 4 reports the average time needed for a reply, defined as the number of calendar days between the post date of the question and its corresponding answer. Column 5 reports the average number of words in each reply. All table values are first computed at the firm level and then averaged across firms.

Panel A in Table 2 reports platform participation statistics for Hu Dong Yi, sponsored by the SZSE. In the first year, each firm received only around 10 questions per quarter. The number of postings increased through to the second quarter of 2015, when investors posted a high of 89 questions per firm-quarter. Although the number of questions tapered off in subsequent years, as of 2017, each SZSE firm continued to receive around 40 questions per quarter. This table also reports descriptive statistics on management responses. Initially, investors needed to wait about three weeks for a reply. As the platform ramped up, companies seemed invest more into the IIP, and the speed of response increased. By the end of 2013, even with sharply increased volume, investors were receiving replies on average within four calendar days. Since 2016, the average reply time has settled to around six calendar days. We observe less intertemporal variation in firm response rates and in the length of their responses. In most quarters, management replied to 90% or more of the questions posted, with each reply averaging 62 Chinese words in length.

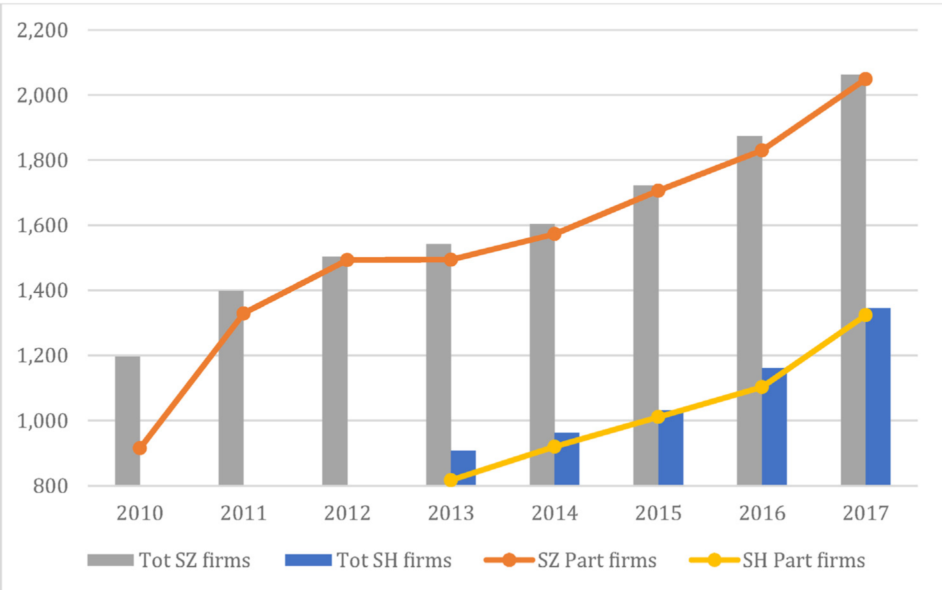

Fig. 1. This figure depicts time-series plots of the number of listed firms and the number of participating firms for SZ Stock Exchange and SH Stock Exchange, respectively. The grey (blue) colored bar graph depicts the total number of listed firms on the SZ (SH) stock exchange. The orange (tan) colored line graph depicts the total number of participating firms from the SZ (SH) stock exchange. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Quarter-by-quarter IIP activities.

Panel A. Shenzhen Stock Exchange (SZSE)

Year-Quarter	Ques Num.	Reply Num.	Reply Rate (Firm Average)	Reply Time (Calendar Days)	Reply Length (Words)
2010Q1	9.61	7.29	94.39%	18.10	65.08
2010Q2	11.44	9.66	89.66%	10.33	67.47
2010Q3	10.40	8.39	84.85%	22.80	62.37
2010Q4	10.28	8.51	82.34%	17.47	65.30
2011Q1	12.96	11.37	89.64%	15.25	67.14
2011Q2	15.84	14.29	91.79%	12.16	73.26
2011Q3	17.62	16.32	93.53%	6.18	74.48
2011Q4	16.37	15.10	93.05%	3.94	78.10
2012Q1	20.27	19.01	94.36%	4.98	72.00
2012Q2	24.58	23.28	93.67%	5.61	74.97
2012Q3	31.57	30.31	94.22%	5.21	73.46
2012Q4	31.17	30.11	95.30%	3.65	73.33
2013Q1	37.98	36.90	95.27%	4.27	66.94
2013Q2	51.20	49.64	95.61%	4.39	66.46
2013Q3	63.18	61.53	96.36%	3.86	64.14
2013Q4	66.92	64.82	96.00%	3.58	61.68
2014Q1	72.39	70.41	96.22%	3.96	58.50
2014Q2	72.06	70.19	95.90%	3.86	60.00
2014Q3	78.47	76.17	95.47%	4.24	56.25
2014Q4	83.09	80.43	95.54%	4.11	53.57
2015Q1	75.28	72.57	94.86%	4.62	51.16
2015Q2	89.18	85.17	93.77%	4.64	49.91
2015Q3	83.55	79.65	93.35%	4.85	51.89
2015Q4	59.39	56.84	93.25%	5.58	51.80
2016Q1	56.68	53.97	92.90%	6.01	51.48
2016Q2	59.38	56.55	93.63%	5.85	54.35
2016Q3	61.74	59.13	93.53%	6.13	52.85
2016Q4	55.23	52.76	93.66%	5.77	52.78
2017Q1	44.38	42.28	92.98%	6.54	54.37
2017Q2	48.17	45.80	93.37%	6.16	57.03
2017Q3	47.58	45.11	93.52%	6.21	59.49
2017Q4	37.82	35.72	93.70%	6.01	61.19
AVERAGE	**45.49**	**43.42**	**93.30%**	**7.07**	**61.96**

Panel B. Shanghai Stock Exchange (SHSE)

Year-Quarter	Ques Num.	Reply Num.	Reply Rate (Firm Average)	Reply Time (Calendar Days)	Reply Length (Words)
2013Q3	8.30	6.13	79.04%	23.12	69.22
2013Q4	11.67	8.61	77.98%	21.86	68.05
2014Q1	10.00	7.72	76.42%	21.67	63.51
2014Q2	8.35	5.96	75.70%	23.30	61.79
2014Q3	10.19	8.47	76.44%	22.78	60.72
2014Q4	10.87	8.53	75.44%	22.73	58.24
2015Q1	11.24	8.94	75.65%	24.90	57.24
2015Q2	14.25	11.43	74.92%	21.43	57.89
2015Q3	13.88	11.00	75.40%	22.53	58.66
2015Q4	10.35	7.89	75.40%	22.79	60.41
2016Q1	10.09	7.72	77.14%	23.56	61.32
2016Q2	10.38	8.30	75.78%	22.48	64.39
2016Q3	11.01	8.85	75.41%	24.03	62.54
2016Q4	10.32	8.34	75.38%	22.34	58.58
2017Q1	9.20	7.24	76.14%	23.78	63.21
2017Q2	14.77	12.54	78.85%	19.13	66.48
2017Q3	18.73	15.73	79.22%	18.97	66.41
2017Q4	19.91	16.68	78.94%	17.29	66.00
AVERAGE	**11.86**	**9.45**	**76.63%**	**22.15**	**62.48**

This table reports firm-level activity on the Shenzhen Stock Exchange (SZSE) interactive platform (Hu Dong Yi) and the Shanghai Stock Exchange (SHSE) interactive platform (e Hu Dong) by quarter. Panel A provides descriptive statistics for the interactive platform launched by the SZSE. Panel B provides descriptive statistics for the SHSE.

Column 1 reports the average number of questions posted on each firm's interactive community. Column 2 reports the average number of answers or responses from management per quarter. Column 3 reports the reply rate, calculated as the number of responses divided by the number of questions for each firm, averaged across all firms. Column 4 reports the average reply time, defined as the number of calendar days between the post date of the question and its corresponding answer. Column 5 reports the average number of words in each reply. All table values are first computed at the firm-level and then averaged across all firms.

Panel B in Table 2 reports the platform activities for e Hu Dong, sponsored by the Shanghai Stock Exchange (SHSE). Column 1 shows that the number of questions on this platform averaged around 12 per firm-quarter, with an apparent pick-up in the last two quarters of 2017, to around 19 per firm-quarter. The average reply time was 22 days, with a notable corresponding reduction in the more recent quarters. Column 3 shows that, for the entire sample period, the reply rate was very stable over a limited range (75%–79%). Overall, compared to the SZSE, investors in SHSE post fewer questions. Managers are less likely to reply to these questions, and, when replying, they also take longer to do so.

3.2. Case studies

In Appendix A, we provide 10 (translated) examples of the type of exchange that occurs on these IIPs. We group these case studies into four categories: (1) clarification questions about a specific transaction, (2) confusion over how certain items or events were treated in financial reports, (3) unreasonable requests about matters not already public (which firms appropriately deflected), and (4) suggestions to management. Collectively, these examples reasonably represent the questions raised.

3.2.1. Type 1: Clarification questions (examples #1 to #4)

In these examples, the investor has heard about an event that affects the firm and seeks clarification on its impact. In each case, the investor exhibits some awareness of the matter but either cannot (or does not wish to) navigate existing disclosures to reach an actionable conclusion. Example #1 pertains to a *performance-contingent* fee that the firm had received during the year. This information is already public, but the investor is unsure how it will impact current earnings. In example #2, an investor wants to know *the total RMB amount for Wind and PV orders* signed during 2017, and states that he or she is “too old” to review reams of announcements. In example #3, an investor observed an increase in the prices of cobalt and tungsten and wants to know *how these price changes impact the company's business*. It seems to us management may have been able to dodge this question by claiming a full answer would involve the release of new information. However, the company chose to answer it by referencing a set of public facts. Our reading is that management used this opportunity to ease concerns over potentially damaging news. In example #4, a firm used the platform to *quell a rumor*. The investor had read a media article accusing the firm of debt concealment in a recent M&A transaction. The firm replied that this information was in fact disclosed and referred the investor to this prior disclosure. The reply also contained belligerent language indicating the firm would “vigorously defend” itself against “irresponsible or malicious reports” in the media.

3.2.2. Type 2: Confusion over accounting treatment (examples #5 to #7)

Examples 5 to 7 pertain to investor confusion over the proper accounting treatment of certain events or transactions. In example #5, the investor read an appraisal report and concluded that the firm overpaid for an acquisition. The firm explained the rudiments of multiple-based valuation and justified the premium it paid. In example #6, the investor wondered why the company's guarantee of a large loan in its subsidiary's books was not recorded as a liability. In example #7, the investor did not understand why a firm paid so much in taxes, given its total profits. In each case, the firm patiently addressed the question and clarified the confusion.

3.2.3. Type 3: Unreasonable requests (examples #8 and #9)

Examples 8 to 9 illustrate inappropriate requests that would require a firm to divulge new information. In example #8, an investor wants to know whether the firm will be paying a stock dividend this year. In example #9, an investor wants a progress report on two projects supported by the Ministry of Science and Technology. In each case the firm politely deferred the question.

3.2.4. Type 4: Suggestions (example #10)

In the last example, an investor does not actually ask a question and only wants to offer some advice on business operations, in this case, various aspects of the firm's R&D. This type of posting does not require any answer or explanation and is usually responded to by a polite acknowledgement.

3.3. A systematic analysis of investor postings

In this subsection, we conduct a more systematic examination of the investor postings. To perform this analysis, we first create a training dataset, consisting of a randomly selected set of 49,659 questions (2% of sample). We manually classify each question in this sample into a $\{5 \times 19\}$ matrix, according to the *nature* of the inquiry (five categories) and the *content* or subject matter of the question (19 categories).[6] We then use the BERT model, a state-of-the-art natural language processing AI algorithm, to systematically analyze the remaining 2,433,285 questions (98% of sample).[7]

[6] Two human researchers were involved in developing this matrix. We checked for consistency across the two individuals by comparing their results over several thousand observations. Where differences in classification were found, these were discussed and reconciled.

[7] Siano (2021) and Siano and Wysocki (2021) also discuss BERT-related applications in an accounting context.

Table 3
Classification of investor postings using an NLP AI model.

Panel A. The Nature of Questions

Type	Frequency	Percent (%)
1. Look for answers or explanations	1,981,749	79.81
2. Correct misunderstanding	6,127	0.25
3. Verify rumors	64,609	2.60
4. Inappropriate questions	17,405	0.70
5. Suggestions or other comments	413,054	16.64
Total	2,482,944	100.00

Panel B. The Content of Questions

Type	Frequency	Percent (%)
1. Financial report	**462,423**	**18.62**
2. Regulation	81,248	3.27
3. External governance	13,919	0.56
4. Asset restructuring	**163,390**	**6.58**
5. Infringement, disputes, lawsuit	18,548	0.75
6. Violation	20,770	0.84
7. Stock trading	**175,614**	**7.07**
8. Insider trading	**101,313**	**4.08**
9. Dividend	**110,338**	**4.44**
10. Financing	**118,321**	**4.77**
11. Investment	**146,867**	**5.92**
12. Operation-operating assets	29,181	1.18
13. Operation-products or business	**538,223**	**21.68**
14. Operation-industry related	**108,588**	**4.37**
15. Operation-macroeconomic environment	63,880	2.57
16. Operation-others	82,318	3.32
17. Corporate governance	**223,283**	**8.99**
18. Stock repurchase	11,137	0.45
19. Others	13,583	0.55
Total	2,482,944	100.00

This table reports the classification of 2,482,944 investor postings based on a Natural Language Processing (NLP) AI algorithm. We use BERT, a state-of-the-art NLP AI model to automatically identify the best-match "Nature" and "Content" category for each question. This model was trained on a dataset consisting of 49,659 questions that were manually categorized by humans.
We construct two separate NLP AI models, one to classify the "Nature" and the other to classify the "Content" of each investor posting. The "Nature" and the "Content" models achieved 92.6% and 80.1% accuracy in a holdout sample, respectively. In other words, the two NLP AI models generated the same classification as the human 92.6% and 80.1% of the time in the hold-out sample, respectively. The top ten topics investors asked about are listed in bold font. The details of how we extracted the training dataset and calibrated the NLP AI model are presented in Appendix B.

As explained in more detail in Appendix B, we construct two separate NLP models, one to classify the "*Nature*" and the other to classify the "*Content*" of each investor posting. The "*Nature*" and the "*Content*" models achieved 92.6% and 80.1% accuracy, respectively. In other words, they generated the same classification as a human, 92.6% and 80.1% of the time, in the hold-out sample.

Table 3 presents the results of our classification for the whole sample using our NLP AI model. Panel A groups these postings into five categories, according to the *Nature* of the inquiry. As this panel shows, a vast majority of these postings (79.81%) relate to specific operating, financial, or investment issues. The second most comment type of posting is comments or suggestions to management (16.64%). This is followed by postings related to rumors that investors would like management to either dispel or verify (2.6%), inappropriate questions (0.7%), and misunderstandings that require correction (0.25%).

Panel B groups these postings into 19 categories based on their *Content* or subject matter. The 10 topics investor most frequently ask about, in descending order, are product or business (21.7%), financial reports (18.6%), corporate governance (9.0%), stock trading (7.1%), asset restructuring (6.6%), investments (5.9%), financing (4.8%), dividends (4.4%), industry-related questions (4.4%), and insider trading (4.1%). As illustrated by the case studies in Appendix A, sometimes investors seek clarifications about the effect of economic events; other times they are simply unsure how certain transactions or events will impact companies' financial reports. Together, these questions broadly reflect the difficulties investors encounter when trying to translate publicly available information into useful inputs for their decisions.

4. Causes and consequences of platform activity

4.1. IIP activities and other information events

In this subsection, we locate IIPs in the context of other firm-related information events that have been widely studied. Corporate information disclosures are magnets for investor attention (Hirshleifer and Teoh, 2003), which can in turn trigger further demand for information. It is therefore reasonable to expect platform activities to interact with other corporate disclosures as well as sell-side analyst reports or news coverage by the financial media. Rather than moving directly to an analysis of the effects of IIP activities, we first investigate the relation between platform activity and several other more traditional firm-related news events.

To conduct this test, we construct a set of indicator variables that assumes a value of 1 when a specific disclosure is issued during the day and 0 otherwise. These variables are (1) *QUESTION* for having at least one question posted on IIP, (2) *REPLY* for having at least one reply posted on IIP, (3) *EA* for an earnings announcement, (4) *EVENTS* for reports of material events, (5) *MEF* for a managerial earnings forecast, (6) *ANARP* for an analyst report, and (7) *MEDIA* for media coverage in a news article. All these variables are derived from information obtained from the China Stock Market and Accounting Research Database (CSMAR) or Chinese Research Data Services Platform (CNRDS) databases. Appendix C contains definitions for all the main variables used in this study.

Panel A in Table 4 presents the pairwise Pearson correlations between these different information disclosure events. Not surprisingly, days with at least one IIP question (*QUESTION=1*) and days with at least one IIP reply (*REPLY=1*) have a positive correlation of 0.372, suggesting these events frequently occur together. The other correlations are also positive but of a lower

Table 4
The relation between IIP activities and other information events.

Panel A. Correlation Matrix

	QUESTION	REPLY	EA	EVENTS	MEF	ANARP	MEDIA
QUESTION	1						
REPLY	0.372***	1					
EA	0.017***	0.008***	1				
EVENTS	0.037***	0.026***	0.246***	1			
MEF	0.018***	0.012***	0.073***	0.184***	1		
ANARP	0.037***	0.018***	0.263***	0.137***	0.065***	1	
MEDIA	0.019***	0.009***	0.048***	0.103***	0.023***	0.085***	1

Panel B. The Effects of Other Information Events on Platform Activities

	Ques Num.	Ques Length	Reply Num.	Reply Length
	(1)	(2)	(3)	(4)
EA	0.0447***	0.1744***	0.0197***	0.0806***
	(12.17)	(12.58)	(6.24)	(7.50)
EVENTS	0.0445***	0.1723***	0.0389***	0.1332***
	(17.76)	(18.53)	(19.34)	(19.80)
MEF	0.0843***	0.3244***	0.0539***	0.1792***
	(12.38)	(12.91)	(8.76)	(8.73)
ANARP	0.0911***	0.3574***	0.0482***	0.1567***
	(15.99)	(17.28)	(11.90)	(11.66)
MEDIA	0.0605***	0.2165***	0.0322***	0.0834***
	(4.92)	(4.98)	(4.17)	(3.69)
Constant	0.2532***	1.0770***	0.1885***	0.7172***
	(65.15)	(72.77)	(64.92)	(71.49)
Observations	3751687	3751687	3751687	3751687
Adjusted R^2	0.003	0.003	0.001	0.001

Panel C. Percentage of Days Having Other Disclosures (Active IIP Periods vs. Entire Period)

	EA	EVENTS	MEF	ANARP	MEDIA
Row 1: Total Sample	1.25%	10.80%	0.46%	3.56%	2.98%
Row 2: QUESTION=1	1.57%	12.50%	0.67%	4.73%	3.54%
Row 3: REPLY=1	1.46%	12.53%	0.65%	4.33%	3.34%
Chi2 test: Row(2)-Row(1)	0.32%***	1.70%***	0.21%***	1.17%***	0.56%***
Chi2 test: Row(3)-Row(1)	0.21%***	1.73%***	0.19%***	0.77%***	0.36%***

This table shows the relation between platform activities and other information events, based on firm-day observations between 2010 and 2017, inclusively. Panel A presents the correlation matrix for different disclosures using: an indicator variable for questions on a firm's IIP (*QUESTION*); an indicator variable for replies on the IIP (*REPLY*); an indicator variable for earnings announcements (*EA*); an indicator variable for material events (*EVENTS*); an indicator variable for managerial earnings forecasts (*MEF*); an indicator variable for analyst reports (*ANARP*); and an indicator variable for news articles that mention the firm (*MEDIA*).

Panel B presents regression results for the influence of other firm-related information events on IIP activities. Proxies for IIP activities in Columns 1−4 respectively are: (1) the number of questions per day (*Ques Num.*), in the natural logarithm form; (2) the total number of words in the posted questions per day (*Ques Length*), in the natural logarithm form; (3) the number of replies posted by the firm per day (*Reply Num.*), in the natural logarithm form; and, (4) the total number of words in the replies posted by the firm per day (*Reply Length*), in the natural logarithm form.

Panel C presents the percentage of days having other firm-related information releases (i.e., *EA*, *EVENTS*, *MEF*, *ANARP*, and *MEDIA*) under three conditions: (a) using the total sample of firm-days, without conditioning on IIP activities (i.e., Total Sample), (b) on days when there is at least one IIP question (i.e., *QUESTION*=1), and (c) when there is at least one IIP reply (*REPLY*=1). The Chi-square tests are presented in last two rows, under the null that daily IIP activities are uncorrelated with the appearance of each of the five other information events. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

magnitude. The highest correlation between an IIP activity (either *QUESTION* or *REPLY*) and another disclosure variable is only 0.037. These findings suggest IIP events are not generally concurrent with other information disclosures and are not subsumed by them.

To further identify the influence of each type of disclosure on platform activities, we conduct a multivariable regression and report the results in Panel B. The dependent variables are four measures of daily IIP activity: (1) the number of questions posted each day (*Ques Num.*), in the natural logarithm form; (2) the total number of words in the questions posted each day (*Ques Length*), in the natural logarithm form; (3) the number of replies posted by the firm on each day (*Reply Num.*), in the natural logarithm form; and (4) the total number of words in the replies posted by the firm each day (*Reply Length*), in the natural logarithm form. The results show that each of the traditional firm-related disclosures relates positively to each of the four IIP variables. However, the low adjusted R-squares (i.e., 0.003 in Columns 1–2 and 0.001 in Columns 3–4) show that, taken together, the other firm-related disclosures explain only a small fraction of the variation in daily IIP activities.

In Panel C, we report the frequency of occurrence for each traditional disclosure event (expressed as a percentage of the total trading days). First, we report the result for the total sample, and then we report separate results for days when at least one question was posted (*QUESTION*=1) and when at least one reply was posted (*REPLY*=1). For example, in the total sample, 1.25% of total trading days contained an earnings announcement. Conditional on at least one question being posted, 1.57% of trading days contained an earnings announcement. The difference of 0.32% is statistically significant, indicating that investors are more likely to post questions on earnings announcement dates. We find similar results with the other firm-related information events, suggesting that communication on the platform is more active on these event dates as well. However, the economic magnitude of the differences in the conditional versus unconditional likelihood of occurrence is small. Taken together, Table 4 results show that these five firm-related information events are positively associated with daily IIP activities but that their ability to explain variations in IIP activities is limited.

4.2. Daily analysis of IIP and investor trading

In this subsection, we examine the relation between daily IIP activity and investor trading. The first measure of trading we use is daily abnormal trading volume (*VOLUME*), defined as the residual from firm-by-firm regressions of daily stock turnover rate on the daily market-level turnover rate (see, for example, Ferris et al. (1988) and Huang et al. (2022)). The second measure we use is daily absolute abnormal return (*ABSRET*), where abnormal return is defined as the residual from a firm-by-firm regression of daily stock return on the daily market return (similar to Ferris et al. (1988) and Ke et al. (2003)).

We estimate the following equation using firm-day observations:

$$Trading_{i,t} = \alpha + \beta IIP_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon_{i,t} \tag{1}$$

where *Trading* is the investors' trading response for firm i on day t, as measured by either abnormal trading volume or absolute abnormal return, and *IIP* is a measure of platform activity for firm i on day t. We use four proxies to measure platform engagement: *Ques Num.*, *Ques Length*, *Reply Num.*, and *Reply Length*. To control for the potential confounding effects of other disclosures, we add a set of indicator variables for five different types of firm-related information events: earnings announcements, reports of material events, managerial earnings forecasts, analyst reports, and media coverage in a news article. We also control for each firm's daily market value of equity and daily market-to-book ratio as well as firm and day fixed effects. Standard errors are clustered by firm to mitigate possible serial correlation in the error term (Petersen, 2009).

The results in Table 5 show that higher levels of IIP activity are associated with more trading. In Panel A, coefficients on all four IIP activity measures are positive and significant at the 1% level, indicating that an increase in IIP activity is associated with an increase in daily abnormal trading volume. Similar to IIP activity, the other five traditional information events also have significantly positive associations with abnormal trading volume. In Panel B, we conduct a similar set of regressions with absolute abnormal return as the dependent variable. These results show that the level of IIP activity has a significant and positive correlation with absolute abnormal return. For parsimony, the estimated coefficients on the five other information events are not tabulated, but each is positive and significant, as expected.

These tests document a positive daily association between IIP activities and investor trading. If IIP activities always occur at the start of the trading day, it would be reasonable to infer that IIP activity affects trading. However, if IIP postings typically occur closer to the end of the trading day, it may be that increased trading causes greater IIP activity.[8] To address this concern, we also regressed day t trading on day t-1 IIP activities, while maintaining all the same control variables. In supplemental (untabulated) tests, we find that day t-1 IIP activity (measured using any of the four proxies) also exhibits a strongly positive relation to both day t abnormal trading volume and day t absolute abnormal return.

Overall, our results show that, controlling for other forms of corporate information events, higher IIP activities are associated with a stronger reaction from market participants. While these findings are consistent with IIP activities serving as a source of information to investors, they could also reflect an increase in noise (or attention-related) trading on days with

[8] We find that while the SHSE seems to report the time that the exchange processed the question (only on workdays), the SZSE seems to report the time that an investor submitted a question (including weekends). It is therefore prudent to assume that the time of posting reported by the SZSE is not necessarily accurate to the hour, only to the day.

Table 5
IIP activity and trading behavior (volume and return volatility).

Panel A. Daily Abnormal Trading Volume

	Dependent Variable=Abnormal Trading Volume			
	(1)	(2)	(3)	(4)
Ques Num.	***0.0034******			
	(24.95)			
Ques Length		***0.0008******		
		(25.58)		
Reply Num.			***0.0020******	
			(21.51)	
Reply Length				***0.0005******
				(22.12)
EA	0.0030***	0.0030***	0.0032***	0.0032***
	(23.96)	(24.20)	(25.58)	(25.58)
EVENTS	0.0024***	0.0024***	0.0024***	0.0024***
	(35.38)	(35.44)	(35.70)	(35.70)
MEF	0.0040***	0.0040***	0.0041***	0.0041***
	(16.69)	(16.77)	(17.23)	(17.28)
ANARP	0.0029***	0.0029***	0.0029***	0.0029***
	(23.45)	(23.48)	(23.84)	(23.84)
MEDIA	0.0085***	0.0085***	0.0086***	0.0086***
	(31.04)	(31.01)	(31.08)	(31.09)
MV	0.0095***	0.0095***	0.0095***	0.0095***
	(20.36)	(20.40)	(20.43)	(20.43)
MB	−0.0003***	−0.0003***	−0.0003***	−0.0003***
	(-3.97)	(-3.97)	(-4.04)	(-4.03)
Constant	−0.2146***	−0.2151***	−0.2152***	−0.2154***
	(-20.52)	(-20.55)	(-20.54)	(-20.55)
Firm FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Observations	3751659	3751659	3751659	3751659
Adjusted R^2	0.087	0.086	0.085	0.085

Panel B. Daily Absolute Abnormal Return

	Dependent Variable=Absolute Abnormal Return			
	(1)	(2)	(3)	(4)
Ques Num.	***0.0645******			
	(16.44)			
Ques Length		***0.0144******		
		(16.23)		
Reply Num.			***0.0298******	
			(10.76)	
Reply Length				***0.0084******
				(11.33)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Observations	3751659	3751659	3751659	3751659
Adjusted R^2	0.188	0.188	0.188	0.188

This table reports the relation between platform activity and investors' daily trading behaviors, based on firm-day observations between 2010 and 2017, inclusively. The dependent variable in Panel A is daily abnormal trading volume, defined as the residual from firm-by-firm regressions of daily stock turnover rate on the daily market-level turnover rate (see, for example, Ferris et al. (1988) and Huang et al. (2022)). The dependent variable in Panel B is daily absolute abnormal return, where abnormal return is defined as the residual from firm-by-firm regressions of daily stock return on the daily market return (similar to Ferris et al. (1988) and Ke et al. (2003)).
For both panels, key variables of interest in Columns 1−4 respectively are: (1) the number of questions per day (*Ques Num.*), in the natural logarithm form; (2) the total number of words in the posted questions per day (*Ques Length*), in the natural logarithm form; (3) the number of replies posted by the firm per day (*Reply Num.*), in the natural logarithm form; and, (4) the total number of words in the replies posted by the firm per day (*Reply Length*), in the natural logarithm form.
We control for other firm-related disclosures using: (1) an indicator variable for earnings announcements (*EA*); (2) an indicator variable for reports of material events (*EVENTS*); (3) an indicator variable for managerial earnings forecast (*MEF*); (4) an indicator variable for analyst reports (*ANARP*); and (5) an indicator variable for news articles mentioning the firm (*MEDIA*). We also control for each firm's daily market value of equity (*MV*) and daily market-to-book ratio (*MB*), as well as firm and day fixed effects. For main variable definitions see Appendix C. Standard errors are calculated using clustering at the firm level. T-statistics are presented in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

higher IIP activities (see, for example, Barber and Odean (2008)). This could happen because IIP activities attract investor attention, leading to higher trading, even if IIP activities do not reduce investor information costs. We try to disentangle these possibilities through the following price-formation tests.

4.3. Daily IIP activities and market liquidity

In these tests, we directly evaluate the extent to which IIP activities are associated with measurable benefits to the firms themselves. Evidence that firms experience improvements in price formation would further support the view that IIP activities help mitigate investor integration costs.

One channel through which IIP may improve firms' market liquidity is by reducing information asymmetry between market participants. The market microstructure literature has long emphasized the effect of information asymmetry on security price formation (e.g., Kyle, 1985; Glosten and Milgrom, 1985). Uninformed investors "price protect" against adverse selection, and this behavior typically manifests in the form of reduced liquidity (Welker, 1995). Disclosures that reduce these costs should improve market liquidity (Leuz and Verrechia, 2000). Therefore, to the extent that IIPs help reduce information asymmetry costs, we should observe an improvement in market liquidity for firms that are more active on the platform.

Panel A in Table 6 examines the effect of interactive communication on daily bid-ask spreads, a common proxy for information asymmetry costs. To construct this panel, we replace the trading measures in Eq. (1) with a measure of daily bid-ask spread (*SPREAD*), computed from daily high and low prices following Corwin and Schultz (2012). The results show a

Table 6
IIP activity and market liquidity.

Panel A. Daily Bid-ask Spread				
	Dependent Variable=Bid-ask Spread			
	(1)	(2)	(3)	(4)
Ques Num.	**−*0.0293********			
	(-14.26)			
Ques Length		**−*0.0066********		
		(-14.16)		
Reply Num.			**−*0.0089********	
			(-5.51)	
Reply Length				**−*0.0022********
				(-5.08)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Observations	3721260	3721260	3721260	3721260
Adjusted R^2	0.143	0.142	0.142	0.142
Panel B. The Price Impact of Trading Volume				
	Dependent Variable = Amihud Illiquidity			
	(1)	(2)	(3)	(4)
Ques Num.	**−*0.0186********			
	(-7.39)			
Ques Length		**−*0.0051********		
		(-8.91)		
Reply Num.			**−*0.0189********	
			(-11.20)	
Reply Length				**−*0.0058********
				(-12.64)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Observations	3751687	3751687	3751687	3751687
Adjusted R^2	0.396	0.396	0.396	0.396

This table reports the relation between platform activity and market liquidity, based on firm-day observations between 2010 and 2017, inclusively. Panel A presents the results of the effects of IIP activities on bid-ask spread. The dependent variable is daily bid-ask spread, computed from daily high and low prices following Corwin and Schultz (2012). Panel B presents the results of the effects of IIP activities on the price impact of trading volume. The dependent variable is the Amihud (2002) illiquidity measure, defined as the ratio of the daily absolute return to the RMB trading volume.

For both panels, the platform activity measures in Columns 1−4 respectively are: (1) the number of questions per day (*Ques Num.*), in the natural logarithm form; (2) the total number of words in the posted questions per day (*Ques Length*), in the natural logarithm form; (3) the number of replies posted by the firm per day (*Reply Num.*), in the natural logarithm form; and, (4) the total number of words in the replies posted by the firm per day (*Reply Length*), in the natural logarithm form.

We control for other firm-related disclosures using: (1) an indicator variable for earnings announcements (*EA*); (2) an indicator variable for reports of material events (*EVENTS*); (3) an indicator variable for managerial earnings forecast (*MEF*); (4) an indicator variable for analyst reports (*ANARP*); and (5) an indicator variable for news articles that mention the firm (*MEDIA*). We also control for firm's daily market value of equity (*MV*) and daily market-to-book ratio (*MB*), as well as firm and day fixed effects. For main variable definitions see Appendix C. Standard errors are calculated using clustering at the firm level. T-statistics are presented in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

Table 7
Quarterly IIP activity and market liquidity.

Panel A. OLS Regression

	SPREAD	AMIHUD
	(1)	(2)
IIP	**−*0.0130******	**−*0.0018******
	(-6.85)	**(-3.78)**
Other Disclosures	YES	YES
Controls	YES	YES
Firm FE	YES	YES
Quarter FE	YES	YES
Observations	64426	64426
Adjusted R^2	0.558	0.389

Panel B. Difference-In-Difference Analysis

	SPREAD	AMIHUD
	(1)	(2)
TREAT* × *POST	**−*0.0405*****	**−*0.0234******
	(-2.03)	**(-3.02)**
Other Disclosures	YES	YES
Controls	YES	YES
Firm FE	YES	YES
Quarter FE	YES	YES
Observations	12480	12480
Adjusted R^2	0.569	0.678

This table examines the relation between platform activity and market liquidity, based on firm-quarter observations. Panel A reports the results from OLS regressions over the period 2010 Q1 to 2017 Q4. Panel B reports the results from a difference-in-differences regression done during the staggered adoption period. For both panels, the dependent variable is either the bid-ask spread (*SPREAD*) or the Amihud illiquidity measure (*AMIHUD*). Bid-ask spread is an estimator from daily high and low prices developed by Corwin and Schultz (2012); and the Amihud (2002) illiquidity measure is defined as the average ratio of the daily absolute return to the RMB trading volume. For each firm, we compute these measures daily, and then average them across all the trading days in a given quarter.
In Panel A, *IIP* is a measure of the overall extent of interactive communication, defined as the mean of four standardized individual measures: the number of questions, question length, the number of replies, and reply length. Higher values of *IIP* reflect more active participation on the interactive platform. In Panel B, *TREAT* is an indicator variable that takes the value of 1 for firms included in the treatment group (defined as actively engaged firms on the Shenzhen stock exchange), and 0 otherwise. *POST* is an indicator for post-event period, equal to 1 if it is year 2011 or year 2012, and 0 if it is year 2008 or year 2009. For main variable definitions see Appendix C. Standard errors are calculated using clustering at the firm level. T-statistics are presented in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

significantly negative coefficient estimate on the IIP variable across all four columns, indicating that the average bid-ask spread is lower on days with higher IIP activities. The evidence here suggests IIP activities are associated with higher market liquidity, potentially due to lower information asymmetry risk.

In Panel B of Table 6, we further examine the market liquidity effects of IIPs using the Amihud (2002) illiquidity measure (*AMIHUD*), defined as the ratio of the daily absolute return to the RMB trading volume. To construct this panel, we replace the trading behavior measures in Eq (1) with the Amihud illiquidity ratio. The results show that the coefficient on IIP measure is negative and significant at the 1% level across four columns. The consistently negative relation indicates that more activity on the interactive platform is associated with a lower price impact for any given level of trading.

The evidence in Table 6 indicates that higher IIP activities are associated with an improvement in market liquidity. To address a possible misalignment in the timing of daily IIP activities, we also regressed day t market liquidity measures on day t-1 IIP activities. In supplemental (untabulated) tests, we find that day t-1 IIP activity (measured using any of the four proxies) also exhibits a strongly negative relation to both day t bid-ask spread and day t Amihud illiquidity ratio.

4.4. Quarterly IIP activities and market liquidity

As a robustness check, we conduct two longer-window tests using quarterly data and control variables more commonly seen in longer-window analyses. First, we examine the effect of IIP activity on bid-ask spread and the Amihud illiquidity ratio, after controlling for the frequency of other firm-related disclosures over each firm-quarter.[9] For parsimony, we use a combined measure of platform activity (*IIP*) for these long-window tests. To construct this combined measure, we standardize each individual measure of platform activity (i.e., *Ques Num.*, *Ques Length*, *Reply Num.*, and *Reply Length*) by subtracting its

[9] In these quarterly regressions, we also control for other determinants of market liquidity identified by prior studies (e.g., Roulstone et al., 2003; Blankespoor et al., 2014; Schoenfeld, 2017), including firm size, financial leverage, market-to-book ratio, intangible assets, institutional ownership, foreign ownership, firm age, state ownership, and share price, as well as indicator variables for low share price, board size, and stock return.

mean and dividing by its standard deviation and compute *IIP* as the mean of these four standardized measures, with higher values representing greater platform activity.[10] The results in Panel A of Table 7 confirm that, at the quarterly level, a higher degree of interactive communication is associated with lower bid-ask spreads and smaller Amihud illiquidity ratios.

Although we find a positive relation between IIP activities and market liquidity, reliable causal inferences may be limited by endogeneity concerns. To address these issues, we exploit the staggered introduction of interactive platforms in the Shenzhen and Shanghai Stock Exchanges, to conduct a difference-in-difference analysis with a propensity-score-matched (PSM) control group. Recall that SZSE launched its IIP in 2010, while SHSE's IIP did not launch until 2013. This staggered adoption allows us to set years 2011 and 2012 as the post-event period,[11] during which direct two-way communication was available for firms listed on the SZSE but not for similar matched firms listed on the SHSE. Correspondingly, 2008 and 2009 comprise our pre-event period. We define the treatment group as SZSE firms that actively participated on the IIP (i.e., firms whose overall IIP activity level was above the median) during the post-event period. We then use PSM to identify a sample of matched control firms from the SHSE.[12] Following Fung, Raman, and Zhu (2017), we test for differences in the market liquidity measures between the treatment and control groups in the pre-adoption period and find the differences are statistically insignificant, consistent with the parallel trends assumption. To conduct a difference-in-differences test, we estimate the following equation:

$$Mkt\_Liq = \alpha + \beta TREAT \times POST + \gamma X + Firm\ Fixed\ Effects + Time\ Fixed\ Effects + \varepsilon \tag{2}$$

where *Mkt_Liq* is a measure of each firm's market illiquidity (either *SPREAD* or *AMIHUD*). *TREAT* is an indicator variable that takes the value of 1 for firms included in the treatment group and 0 otherwise. *POST* is an indicator for the post-event period, which equals 1 when the year is 2011 or 2012 and 0 otherwise. The major variable of interest is the interaction term between the treatment group and the post-period (i.e., $TREAT \times POST$). A negative coefficient indicates treatment firms experienced a greater reduction in market illiquidity (i.e., a greater increase in liquidity) than control firms.

Panel B of Table 7 presents the results for our difference-in-differences analysis. As shown, the coefficient on $TREAT \times POST$ is -0.0405 ($t = -2.03$) for the bid-ask spread measure and -0.0234 ($t = -3.02$) for the Amihud illiquidity ratio. This result further supports our earlier finding that direct interactive communication between managers and investors can significantly improve market liquidity.[13]

4.5. IIP activity and the informativeness of price for future earnings

Having documented the effect of IIP activities on market liquidity, we further explore the effect of interactive communication on firms' price informativeness—the information content of stock prices with respect to future firm fundamentals. Conceptually, liquidity can be an importance determinant of the predictability of fundamentals (see, for example, Kerr et al., 2020). Specifically, when liquidity improves for a firm, information can be more readily incorporated into its stock price, increasing the informativeness of its stock price with respect to future fundamentals, such as reported earnings.

To test this hypothesis, we follow Lee and Watts (2021) and estimate the following regression using firm-quarter observations:

$$CAR_{i,t}^{[-60,-1]} = \beta_0 + \beta_1 SUE_{i,t} \times IIP_{i,t} + \beta_2 SUE_{i,t} + \beta_3 IIP_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon \tag{3}$$

where the dependent variable is the market-adjusted return of the firm computed over days t-60 to t-1, relative to each quarter t's earnings announcement date. *SUE* is standardized unexpected earnings for quarter t, defined as quarter t earnings minus quarter t-4 earnings, scaled by market value on day t-60. The main variable of interest is β_1, the coefficient on the interaction term between standardized unexpected earnings and IIP activities. A positive coefficient on β_1 indicates greater interactive communication between managers and investors is associated with an increase in the ability of pre-earnings announcement returns to predict future SUEs. As before, we use four proxies to measure platform engagement: *Ques Num.*, *Ques Length, Reply Num.*, and *Reply Length*, each measured over days t-60 to t-1 relative to quarter t's earnings announcement date. Consistent with our short-window analyses, we control for other firm-related disclosures (managerial earnings forecasts, reports of material events, analyst reports, and media coverage in a news article), each measured over days t-60 to t-1 relative to quarter t's earnings announcement date. In addition, we follow Lee and Watts (2021) and control for

10 The results are similar if we use individual IIP measures instead of the composite.

11 We exclude 2010, the year the program was first initiated, because it takes time to promote and to familiarize for both investors and participating firms with the usage of this new technology. Initially, many firms did not have platform accounts or did not know how to use it.

12 To implement PSM, we first estimate a logit regression, where the dependent variable equals 1 if a firm is classified as treated and 0 otherwise, and the independent variables are our matching characteristics. Similar to DeFond et al. (2015), we include all control variables in quarterly OLS regressions in the PSM model to ensure that all known factors that potentially affect market liquidity are similar between the treatment and control samples. In the second step, we use the estimated coefficients to calculate the predicted probability (i.e., propensity score) for each firm and match each treatment firm to the control firm using the nearest-neighbor technique.

13 These results depend on which SZSE firms are included in the treatment group. The treatment group in our analysis consists of SZSE firms with an overall IIP activity level that is above the median. As a pseudo-test, we reran this analysis using all SZSE firms as the treatment group and found no significant results. This further suggests that the results are driven by SZSE firms that actively participated on the IIP.

Table 8
IIP activity and the informativeness of price for future earnings.

	Dependent Variable=CAR$^{[-60,-1]}$			
	(1)	(2)	(3)	(4)
Ques Num. × ***SUE***	***0.2532******			
	(7.67)			
Ques Length × ***SUE***		***0.1042******		
		(7.13)		
Reply Num. × ***SUE***			***0.2101******	
			(6.60)	
Reply Length × ***SUE***				***0.0778******
				(5.84)
SUE	0.1568**	0.1225*	0.2802***	0.2879***
	(2.41)	(1.70)	(4.81)	(4.72)
Ques Num.	−0.5301***			
	(-5.95)			
Ques Length		−0.1630***		
		(-4.12)		
Reply Num.			−0.4080***	
			(-4.97)	
Reply Length				−0.1106***
				(-3.15)
EVENTS	−0.0044	−0.0084	−0.0103	−0.0129
	(-0.05)	(-0.09)	(-0.11)	(-0.14)
MEF	−0.1443	−0.1762	−0.1536	−0.1774
	(-0.45)	(-0.55)	(-0.48)	(-0.56)
ANARP	1.1975***	1.1943***	1.1947***	1.1933***
	(14.22)	(14.17)	(14.19)	(14.17)
MEDIA	2.3582***	2.3393***	2.3419***	2.3276***
	(15.19)	(15.05)	(15.06)	(14.97)
SIZE	3.9193***	3.9214***	3.9298***	3.9349***
	(12.20)	(12.18)	(12.21)	(12.20)
MB	0.7174***	0.7211***	0.7187***	0.7224***
	(14.58)	(14.65)	(14.59)	(14.66)
GROWTH	−0.0314***	−0.0308***	−0.0316***	−0.0312***
	(-4.90)	(-4.81)	(-4.93)	(-4.86)
ROA	−0.0731	−0.0678	−0.0693	−0.0624
	(-1.14)	(-1.06)	(-1.08)	(-0.97)
Constant	−86.1126***	−86.0463***	−86.4767***	−86.5447***
	(-12.02)	(-11.98)	(-12.05)	(-12.03)
Firm FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Observations	52449	52449	52449	52449
Adjusted R^2	0.140	0.139	0.139	0.139

This table presents results from an analysis of the effect of IIP activities on the informativeness of pre-announcement returns with respect to upcoming earnings news. Specifically, we estimate:
$CAR_{i,t}^{[-60,-1]} = \beta_0 + \beta_1 SUE_{i,t} \times IIP_{i,t} + \beta_2 SUE_{i,t} + \beta_3 IIP_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon$
Where dependent variable is market-adjusted return of the firm computed over days t-60 to t-1 relative to each quarter t's earnings announcement date. SUE is standardized unexpected earnings, calculated as the current earnings minus earnings from the corresponding quarter a year ago and scaled by market value on day t-60.
IIP measures in Columns 1−4 respectively are: (1) the number of questions over days t-60 to t-1 relative to each quarter t's earnings announcement date (*Ques Num.*), in the natural logarithm form; (2) the number of words in posted question over days t-60 to t-1 relative to each quarter t's earnings announcement date (*Ques Length*), in the natural logarithm form; (3) the number of replies posted by the firm over days t-60 to t-1 relative to each quarter t's earnings announcement date (*Reply Num.*), in the natural logarithm form; (4) the number of words in reply posted by the firm over days t-60 to t-1 relative to each quarter t's earnings announcement date (*Reply Length*), in the natural logarithm form.
We control for other firm-related disclosures using: (1) the number of reports of material events over days t-60 to t-1 relative to each quarter t's earnings announcement date (*EVENTS*), in the natural logarithm form; (2) the number of managerial earnings forecasts over days t-60 to t-1 relative to each quarter t's earnings announcement date (*MEF*), in the natural logarithm form; (3) the number of analyst reports over days t-60 to t-1 relative to each quarter t's earnings announcement date (*ANARP*), in the natural logarithm form; and, (4) the number of news articles mentioning the firm over days t-60 to t-1 relative to each quarter t's earnings announcement date (*MEDIA*), in the natural logarithm form.
In addition, we follow Lee and Watts (2021) and control for firm size (*SIZE*), market-to-book ratio (*MB*), asset growth (*GROWTH*) and return on asset (*ROA*), as well as firm and quarter fixed effects. For main variable definitions see Appendix C.
These tests are based on firm-quarter observations between 2010 and 2017, inclusively. T-statistics are presented in parentheses. Standard errors are calculated using clustering at the firm level. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

firm size, market-to-book ratio, asset growth, and return on assets. Finally, the regression also includes firm and quarter fixed effects, with standard errors corrected for clustering at the firm level.[14]

[14] We also re-ran these tests with future SUE interacted with: (a) other information events, and (b) all the control variables. All four variables of interest remain statistically significant under these alternative specifications.

Table 9
Changes in financial statement-related activities on the IIPs surrounding the mandatory adoption of new accounting standards.

	FS Ques Num.	FS Reply Num.	FS Ques Proportion	FS Reply Proportion
	(1)	(2)	(3)	(4)
AS Change	***0.1295****	***0.1011****	***0.0354****	***0.0312****
	(9.22)	***(7.00)***	***(5.58)***	***(4.99)***
EVENTS	−0.0182***	−0.0161***	−0.0115***	−0.0106***
	(-4.56)	(-3.90)	(-6.31)	(-5.64)
MEF	0.0661***	0.0788***	0.0056	0.0053
	(3.53)	(4.11)	(0.78)	(0.70)
ANARP	0.0254***	0.0251***	0.0024	0.0028*
	(5.59)	(5.40)	(1.52)	(1.77)
MEDIA	0.0102	0.0060	−0.0146***	−0.0141***
	(1.64)	(0.97)	(-6.38)	(-5.98)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year & Seasonal FE	YES	YES	YES	YES
Observations	62033	62033	50137	44943
Adjusted R^2	0.464	0.460	0.146	0.155

This table presents results on the effect of changes in accounting standards on financial statement-related IIP activities. Effective July 2014, the Accounting Standards Board of China formally revised five existing standards and adopted three new standards. The revised accounting standards include: (1) Accounting Standard for Business Enterprises (ASBE) 30.—Presentation of Financial Statement; (2) ASBE 9.—Employee Benefits; (3) ASBE 33.— Consolidated Financial Statements; (4) ASBE 2.—Long-term Equity Investment; and (5) ASBE 37.— Presentation of Financial Instruments. In addition, the newly introduced accounting standards include: (1) ASBE 39.—Measurement of Fair Value; (2) ASBE 40.—Joint Venture Arrangements; and (3) ASBE 41.—Disclosure of Interests in Other Entities.

The dependent variables are proxies for financial statement-related IIP activities. Presented in Columns 1−4 respectively, these variables are: (1) the number of financial statement-related questions over days t to t+30 relative to each quarter t's earnings announcement date (*FS Ques Num.*), in the natural logarithm form; (2) the number of financial statement-related replies over days t to t+30 relative to each quarter t's earnings announcement date (*FS Reply Num.*), in the natural logarithm form; (3) the ratio of the number of financial statement-related questions to the number of total questions over days t to t+30 relative to each quarter t's earnings announcement date (*FS Ques Proportion*); and (4) the ratio of the number of financial statement-related replies to the number of total replies over days t to t+30 relative to each quarter t's earnings announcement date (*FS Reply Proportion*).

Our variable of primary interest (*AS Change*) is equal to 1 for 2014 Q3 observations, and 0 otherwise. We control for other firm-related disclosures using: (1) the number of reports of material events over days t to t+30 relative to each quarter t's earnings announcement date (*EVENTS*), in the natural logarithm form; (2) the number of managerial earnings forecasts over days t to t+30 relative to each quarter t's earnings announcement date (*MEF*), in the natural logarithm form; (3) the number of analyst reports over days t to t+30 relative to each quarter t's earnings announcement date (*ANARP*), in the natural logarithm form; and, (4) the number of news articles mentioning the firm over days t to t+30 relative to each quarter t's earnings announcement date (*MEDIA*), in the natural logarithm form. For main variable definitions see Appendix C. T-statistics are presented in parentheses. Standard errors are calculated using clustering at the firm level. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-tailed).

Our results in Table 8 show that the cumulative pre-earnings announcement return is more positively correlated with future standardized unexpected earnings when investors and managers are more active on the interactive platform. This finding is robust and highly significant across all four measures of IIP activity (with t-statistics ranging from 5.84 to 7.67). Evidently higher IIP activities in a quarter are associated with greater price informativeness with respect to the earnings surprise in the upcoming quarterly earnings announcement. Our finding is consistent with IIP activities effectively reducing investor information processing costs and thus accelerating the price discovery associated with future earnings.

4.6. IIP activity after the mandatory adoption of new accounting standards

As a final test, we examine changes in IIP activity associated with the mandatory adoption of new accounting standards. Mandatory adoptions of new standards are, for the most part, non-information events that do not change the economics of the business. However, integration costs are likely higher in the period immediately following adoption as investors try to understand and act on firms' financial results under the new rules. Therefore the introduction of new standards offers an attractive setting for examining changes in integration costs due to increased accounting complexity.

In July 2014, the Accounting Standards Board of China formally revised five accounting standards and adopted three new ones.[15] We examine the effect of this major change in reporting standards on IIP activities by estimating the following regression:

$$FS\_IIP_{i,t} = \alpha + \beta AS\ Change_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon \quad (4)$$

[15] The revised accounting standards are (1) Accounting Standard for Business Enterprises (ASBE) 30.—Presentation of Financial Statement; (2) ASBE 9.—Employee Benefits; (3) ASBE 33.— Consolidated Financial Statements; (4) ASBE 2.—Long-term Equity Investment; and (5) ASBE 37.— Presentation of Financial Instruments. In addition, the three newly introduced accounting standards are (1) ASBE 39.—Measurement of Fair Value; (2) ASBE 40.—Joint Venture Arrangements; and (3) ASBE 41.—Disclosure of Interests in Other Entities.

where the dependent variable is a measure of financial statement-related IIP activities measured over days t to t+30, relative to each quarter t's earnings announcement date. We use four different proxies for financial statement-related activities, corresponding to (1) the number of financial statement-related questions (*FS Ques Num.*), in the natural logarithm form; (2) the number of financial statement-related replies (*FS Reply Num.*), in the natural logarithm form; (3) the ratio of the number of financial statement-related questions to the number of total questions (*FS Ques Proportion*); and (4) the ratio of the number of financial statement-related replies to the number of total replies (*FS Reply Proportion*). Our variable of interest (*AS Change*) is a quarterly indicator that equals 1 for third quarter of 2014 observations and 0 otherwise. As before, we control for other forms of firm-related disclosures and variables that studies (e.g., Frankel et al., 1999; Drake et al., 2012; Bourveau and Schoenfeld, 2017) suggest may affect corporate disclosure. Firm, year, and seasonal fixed effects are also included.

Our results in Table 9 show that, in the fiscal quarter after the new standards came into effect, there was an increase of 12.95% in the number of financial statement-related questions and an increase of 10.11% in the number of financial statement-related replies. During this quarter, the proportion of total questions (replies) that dealt with financial statement-related topics increased by 3.54% (3.12%). These findings indicate that changes in accounting standards can increase information processing costs for investors, leading to an increase in both the number and the proportion of financial statement-related questions. In addition, the evidence also lends support for the important role of interactive communication in facilitating information integration.

5. Conclusion

This study analyzes the causes and consequences of a new form of interactive corporate communication. Between 2010 and 2017, the vast majority of Chinese publicly listed firms began using an online platform to interact with their investors. We examine the nature and content of these exchanges and link platform activities to market reactions, after controlling for other corporate disclosures and news events. We also examine the empirical link between platform activities and firms' market liquidity and price informativeness.

Our analyses show that (a) most investor questions reflect difficulties in integrating information that is already public; (b) controlling for other firm-related information events, higher platform activity is associated with greater trading volume and return volatility; (c) higher platform activity is associated with improvements in market liquidity and price informativeness, and (d) the introduction of new accounting standards correlates with increases in IIP activities, particularly financial statement-related postings. Collectively, these results suggest that this new form of dialogue can reduce investor information costs and improve corporate communications, with measurable benefits to firms' price formation.

These findings add to a growing stream of literature that examines direct interactions between managers and capital market participants. Studies show such interactions can improve the informational efficiency of financial markets. However, these studies focus mainly on highly visible and potentially influential market participants, such as institutional investors and sell-side analysts (e.g., Kirk and Markov, 2016; Cheng et al., 2016; Bushee et al., 2011). We complement this literature by showing that direct communication via IIPs may be particularly valuable to ordinary investors and that this form of investor engagement can yield significant benefits to listed firms.

Our study also relates to a nascent but important literature that examines the determinants and consequences of investor relations, or IR, programs (Bushee and Miller, 2012; Kirk and Vincent, 2014). Empirical work in this area tends to focus on the economic causes and consequences associated with the establishment of an IR program (Firth et al., 2019). Our analyses extend this literature by documenting the causes and consequences of direct engagement with investors through an online platform. Our results suggest that firms may benefit from incorporating some element of dialogue into future IR programs.

We believe these findings are also relevant to regulators concerned with reporting clarity and investor protection. Our findings suggest that even plainly written disclosures can cause confusion and that dialogue may improve investor comprehension. These results also speak to the SEC's expressed desire to level the playing field across investor classes.[16] Current regulations aimed at mitigating discrimination across classes of investors focus mainly on increasing retail investor awareness of and access to firm disclosures. Our results suggest that a more important issue facing retail investors may be integration costs. To this end, our findings suggest that efforts to reduce such costs, such as the introduction of IIPs, can benefit both retail investors and listed firms.

An important caveat is that our results are based on Chinese data and may not generalize to other jurisdictions. Two aspects of the Chinese setting in particular deserve highlighting. First, firms' participation in this program is quasi-mandatory. Although the stock exchanges do not force member firms to participate, they monitor each firm's level of engagement and publish these rankings. They also provide "awards" (of minimal economic value and better viewed as bragging rights) to firms that are most responsive to their investors. Second, investor participation is not entirely anonymous (i.e., although the identity of the questioner is not publicly posted, as the sponsor of the platform, either the SZSE or the SHSE, can trace the question to a specific user cell phone as needed). Presumably the monitoring role of Chinese stock exchanges affects behavior on both sides of this platform, but it is difficult to know how different the results would be absent such monitoring.

[16] On June 3, 2009, the SEC announced the formation of the Investor Advisory Committee (Lawrence, 2013), with an expressed goal of giving individual investors a greater voice in the commission's work and improving the financial reporting environment for the benefit of individual investors (SEC, 2009). Among the SEC's five current initiatives for investor protection, four emphasize benefits to retail investors (see Strategic Plan for FY, 2018 through FY, 2022).

In this study, we made a research design choice to focus on short-window tests (daily or quarterly intervals). The main advantage of a short-window design is that it is easier to identify and isolate the effect of IIP activities on investor behavior and market metrics. Because we have millions of individual IIP events, these short-window tests also have large statistical power. The main disadvantage is that some important consequences of IIP engagement may not be captured by short-window market reactions. As noted by BDM (2020), the influence of improved disclosure processing on market outcomes “can be cumulative and have uncertain timing; for example, it can take multiple periods to build a reputation for transparency” (p. 34). It is also difficult to make statements about the long-run effect or the economic magnitude of benefits to participating firms without a longer window analysis. We leave this to future research.

Recent years have witnessed a strong trend toward evidence-based policymaking, wherein policy decisions are made on the basis of best available scientific and empirical evidence (Leuz, 2018). The aforementioned caveats notwithstanding, our findings suggest interactive communication platforms are an important development in investor communications, one that could lead to new ways to improve reporting clarity, protect retail investors, and improve the quality of equity markets.

Appendix A. Examples of Platform Dialogue

In this appendix, we present examples of the type of exchange that takes place on the Investor Interactive Platforms (IIPs). We translated the original Chinese into English for this purpose. These examples are selected for illustrative purposes and are reasonably representative of the types of postings commonly observed on the IIPs.

Example 1. Specific line item (information already public, but investor unsure of accounting treatment)

科陆电子 [Firm ID: 002121]

Questions: The company recently received compensation for its acquired firm failing to meet the performance commitment (about RMB 7.8 million). Can this compensation be recognized in the net profit?

Answer: Yes, RMB 7.8 million will be recognized in the net profit of this year.

Example 2. Specific Line Item (total reported Wind & PV orders)

九洲电气 [Firm ID: 300040]

Questions: Excuse me. I'm too old to look through your huge volumes of announcements. I would just like to ask about the total RMB amount of the orders you have signed for in 2017 that is related to wind and PV (photovoltaic) power generation. Considering that the regulatory curtailment of wind and PV power generation is becoming more prevalent, please control for these relevant risks.

Answers: Thanks for your attention! Our company has already signed about 2.5 billion RMB in contracts for wind and PV power generation during 2017.

Example 3. Industry-related (effect of an increase in input prices on performance)

格林美 [Firm ID: 002340]

Question: The recent increase in the prices of cobalt and tungsten has led to higher input costs for cement carbide producers. Please talk about the potential impacts on the company's cement carbide business.

Answer: Thank you for your attention! The cement carbide industry is a relatively mature industry with a growth rate of 8–10% per year. This year we witnessed a rise in the prices of cobalt and tungsten, especially for cobalt, driving the input price of cement carbide products. However, the average proportion of cobalt contained in cement carbide products is only around 15%, so these price changes will have little impact on the price of our end products. In addition, our company recovers cement carbide waste as part of cobalt and tungsten raw materials, ensuring the effective recycling of major metals in the cement carbide business.

Example 4. Rumors (asking for clarification on a rumored debt concealment problem)

金城医药 [Firm ID: 300233]

Question: Some media have accused your company of concealing a huge amount of debt during the acquisition of Beijing Laneva Pharmaceutical Co., Ltd. (hereafter Laneva). Laneva was sued for defaulting on construction fees of 71 million. Why didn't your company disclose this material information (Report link: http://finance.sina.com.cn/roll/2017-04-28/doc-ifyetwtf8843011.shtm)?

Answer: Dear investor, thanks for your attention. The relevant information about Laneva and its original shareholders has already been disclosed in our reorganization report. For the litigation mentioned in that report, the two parties have reached a settlement and the lawsuit has been withdrawn. Our company has also provided detailed disclosure of the settlement in the progress report of the litigation. If this event causes any unforeseen loss to the company, we will pursue recourse against the original shareholders of Laneva and prevent our investors' interests from being infringed upon. As a listed company, we are always open to media supervision. However, in the case of irresponsible or malicious reports, we will take legal actions to protect our reputation and our investors’ interests.

Example 5. Misunderstandings (confusion over M&A premium calculation)

中国长城 [Firm ID: 000066]

Questions: According to the appraisal report, the book value of net asset for China Electronics Finance Co., Ltd. (hereafter CEC) is 2.772 billion, and thus 15 percent of firm's shares is worth 415.8 million. The purchase price in the plan is about 507 million, with a premium of more than 20%. Please explain the high premium and your motivation to purchase 15 percent of CEC’ shares at this high price.

Answer: Hi, dear investors! According to the audit report issued by Lixin Certified Public Accountants LLP, the asset appraisal company reported that CEC has a book equity value of 2.843 billion and a warranted PB ratio is established to be 1.19, based on an evaluation of comparable cases. Therefore, the total value of shareholders' equity is 3.383 billion. On this basis, the transfer price for the 15% equity share of CEC was established as 507.46 million. Please refer to the appraisal report on the CNINF website for details. The aim of this purchase is to fully utilize the finance platforms of CEC to realize effective fund management, and to accelerate firm growth via optimizing our asset mix and business structure.

Example 6. Misunderstandings (confusion over debt guarantees vs. outstanding debt)

亿纬锂能 [Firm ID: 300014]

Questions: The company guarantees the payment of 2.16 billion of its subsidiary's debt. However, the total debt of the company is only 2.29 billion, which seems unrealistic. Could you explain?

Answers: The company has already signed a financial guarantee agreement, according to which the company is obligated to pay up to 2.16 billion if the subsidiary defaults on its debts, including: bank credit granting agreement, loan contract with Jingmen High-tech Industrial Investment Co., Ltd., the letter of credit for the equipment import. Within the credit line, the subsidiary can apply for the funding according to its needs. Therefore, the guarantee is not the loan or debt of the company and thus will not be reflected in the accounts of debts. For details about the company's borrowing, please refer to the corporate annual financial statements.

Example 7. Misunderstandings (confusion over tax rates and reported taxes)

华铁股份 [Firm ID: 000976]

Questions: From the annual report, I find that the total profit is 92 million and the corporate income tax is 63.55 million, which means that the tax rate amounts to nearly 70%! Why?

Answers: The total profit is the consolidated data after the merger of Tong Dai Control (Hong Kong) Limited (hereafter Tong Dai). The parent company reported a negative profit and thus didn't have to pay the corporate income tax. The 63.55 million in the financial report refers to the income tax paid by the subsidiaries of Tong Dai, whose profit is 346.87 million for the period between the merger date and the year end, indicating that the tax rate is less than 20%.

Example 8. An Unreasonable Request (for undisclosed information)

国光股份 [Firm ID: 002749]

Questions: I wonder whether the company will pay stock dividend this year. Only paying cash dividend can keep the stock price at a high level, but may lead investors to lose confidence in the company.

Answer: According to the related rules concerning interactive platform issued by Shenzhen Stock Exchange, we actively communicate with investors with serious and responsible attitude, but cannot divulge any undisclosed material information during the communication. All mandatory information will be accurately, completely, and timely disclosed in designated media (e.g., http://www.cninfo.com.cn/), according to the information disclosure requirements.

Example 9. An Unreasonable Request (for undisclosed information)

大恒科技 [Firm ID: 600288]

Questions: Please disclose the details about the progress and plan of two projects supported by the Ministry of Science and Technology.

Answers: Our company has already disclosed related information in the financial reports. For undisclosed information, we can't communicate with investors on the interactive platforms, according to the rules concerning e Hu Dong issued by Shanghai Stock Exchange.

Example 10. Suggestions.

京运通 [Firm ID: 601908]

Questions: In my opinion, your company has good prospects. Meanwhile, I would like to give your company some advice: 1) Conduct research on the application of solar energy in the field of solar-powered automobile, electric vehicles and even aircrafts etc., in addition to power station; 2) Conduct research on the application of graphene in the field of solar energy. Specifically, the combination of graphene and crystalline silicon can achieve higher efficiency, thus finally leading to the complete replacement of crystalline silicon in the future; 3) Expedite the development of environmental business, especially in the Beijing-Tianjin-Heibei region.

Answers: Hi, dear investor! Your feedback and recommendations will be given to the appropriate leaders in our firm. Thank you!

Appendix B. Question Classification using NLP

1) Manual Classification of Training Data

We extract the training data in three steps. First, we assign a unique ID to each question in the database. This is done by first sorting all questions by ***firm ID,*** then sorting the questions within each firm by ***time stamp***. Second, we generate a random "seed" between 1 and 50, and use it to make our first sample selection. Finally, beginning with the first selection, we select every 50th question in the database in sequence. Because there are 2,482,944 questions in our overall sample, the resulting training dataset consists of 49,659 questions.

Two researchers then manually classified the questions in this training sample. To ensure consistency and to develop a uniform approach, each researcher first categorized a sample of several thousand observations. These results are then compared across the researchers and any differences are reconciled. The process is then continued by one researcher alone for the remaining observations. The results are presented in Table B1 below.

Table B.1
Manual classification

Panel A The Nature of Questions

Type	Frequency	Percent (%)
1. Look for answers or explanations	38,426	77.38
2. Correct misunderstanding	830	1.67
3. Verify rumors	1,162	2.34
4. Inappropriate questions	591	1.19
5. Suggestions or others	8,650	17.42
Total	49,659	100

Panel B The Content of Questions

Type	Frequency	Percent (%)
1. Financial report	9,151	18.43
2. Regulation	1,590	3.20
3. External governance	352	0.71
4. Asset restructuring	3,115	6.27
5. Infringement, disputes, lawsuit	405	0.82
6. Violation	438	0.88
7. Stock trading	3,443	6.93
8. Insider trading	1,928	3.88
9. Dividend	2,117	4.26
10. Financing	2,209	4.45
11. Investment	3,017	6.08
12. Operation-operating assets	635	1.28
13. Operation-products or business	10,434	21.01
14. Operation-industry related	2,272	4.58
15. Operation-macroeconomic environment	1,204	2.42
16. Operation-others	1,799	3.62
17. Corporate governance	4,804	9.67
18. Stock repurchase	232	0.47
19. Others	514	1.04
Total	49,659	100

2) Natural Language Processing AI model

We use BERT, a state-of-the-art family of Natural Language Processing AI models, to classify the remaining 2,433,285 questions in our sample. Recent research shows that BERT's performance can in fact be superior to humans on the general language understanding benchmark.[17]

For each question, we first feed the raw text through a multi-layer bidirectional Transformer model (Vaswani et al., 2017) called $\text{BERT}_{\text{LARGE}}$ (Devlin et al., 2018), which uses 24 encoders with 16 bidirectional self-attention heads to extract the representations. We then pre-training this model by following the training procedure of RoBERTa (Liu et al., 2019) as applied to Dynamic Masking,[18] while disabling the Next Sentence Prediction loss feature. A single layer fully-connected neural network is applied to the representations to predict the probability of a given question belonging to each category. We then assign each question to the category associated with the highest probability.

To conduct this analysis, we load from a Chinese BERT model developed by Cui et al. (2019), which is trained on a combination of the Chinese WIKIPEDIA and other Chinese text corpus including news and question-and-answer on the websites. The classification model is trained on the 2% manual labels (i.e., 49,659 manually classified questions) in which 44,582 questions are used for training, and 5,077 questions are held for evaluation.

[17] https://super.gluebenchmark.com/leaderboard.

[18] Dynamic masking: BERT relies on randomly masking and predicting words in the sentence. The original BERT implementation performed masking once during data preprocessing, resulting in a single static mask. To avoid using the same mask for each training instance in every epoch, RoBERTa duplicates the training data 10 times so that each sequence is masked in 10 different ways during training.

We construct two separate NLP models, one to classify the "Nature" and the other to classify the "Content" of each investor posting. The "Nature" and the "Content" models are trained on Nvidia A100 GPU for 3 epochs, and achieved 92.6% and 80.1% accuracy, respectively. In other words, these two NLP AI models generated the same classification as the human 92.6% and 80.1% of the time, respectively, in the hold-out sample.

Appendix C. Main Variable Definitions

Variable name	Variable definition
Ques Num.	The number of questions posted on a firm's IIP, in the natural logarithm form.
Ques Length	The total number of words in the questions posted on a firm's IIP, in the natural logarithm form.
Reply Num.	The number of replies posted by the firm on its IIP, in the natural logarithm form.
Reply Length	The total number of words in the replies posted by the firm on its IIP, in the natural logarithm form.
IIP	A composite measure of platform activity, defined as the mean of four standardized measures: *Ques Num.*, *Ques Length*, *Reply Num.*, and *Reply Length*. We standardize each variable by subtracting its mean and dividing by its standard deviation. Higher values of IIP reflect more active participation on the platform.
EA	Indicator variable for an earnings announcement during the day.
EVENTS	In daily analyses, EVENTS=1 if the firm issued a report of material events during the day, 0 otherwise; In longer horizon analyses, EVENTS = ln (1 + the number of reports of material events issued during period).
MEF	In daily analyses, MEF=1 if a managerial earnings forecast is issued during the day, 0 otherwise; In longer horizon analyses, MEF = ln (1 + the number of managerial earnings forecasts issued during period).
ANARP	In daily analyses, ANARP=1 if one or more analyst reports are issued during the day, 0 otherwise; In longer horizon analyses, ANARP = ln (1 + the number of analyst reports issued during period).
MEDIA	In daily analyses, MEDIA=1 if the firm is mentioned in one or more news articles during the day, 0 otherwise; In longer horizon analyses, MEDIA = ln (1 + the number of news articles mentioning the firm during period).
VOLUME	Daily abnormal trading volume, defined as the residual from a firm-by-firm regression of daily stock turnover rate on the daily market-level turnover rate (see, for example, Ferris et al. (1988) and Huang et al. (2022)).
ABSRET	Daily absolute abnormal return, where abnormal return is defined as the residual from a firm-by-firm regression of daily stock return on the daily market return (similar to Ferris et al. (1988) and Ke et al. (2003)).
SPREAD	Average relative bid-ask spread. For daily analyses, this variable is computed from daily high and low prices following Corwin and Schultz (2012). For quarterly analyses, this variable represents the average across all trading days during the quarter.
AMIHUD	Amihud (2002) illiquidity measure, defined as the ratio of the daily absolute return to the RMB trading volume. For quarterly analyses, this variable represents the average across all trading days during the quarter.
$CAR^{[-60,\,-1]}$	Cumulative market-adjusted return of the firm computed over days t-60 to t-1 relative to each quarter t's earnings announcement date. Measured in percent.
SUE	Standardized unexpected earnings, calculated as the current quarter earnings minus earnings from the corresponding quarter a year ago and scaled by market value on day t-60 relative to earnings announcement date. Measured in percent.
AS Change	Indicator variable for the mandatory adoption of new accounting standards, equaling 1 for 2014 Q3 observations, and 0 otherwise.
FS Ques Num.	The number of financial statement-related questions over days t to t+30 relative to each quarter t's earnings announcement date, in the natural logarithm form.
FS Reply Num.	The number of financial statement-related replies over days t to t+30 relative to each quarter t's earnings announcement date, in the natural logarithm form.
FS Ques Proportion	The ratio of the number of financial statement-related questions to the number of total questions over days t to t+30 relative to each quarter t's earnings announcement date.
FS Reply Proportion	The ratio of the number of financial statement-related replies to the number of total replies over days t to t+30 relative to each quarter t's earnings announcement date.

References

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. J. Financ. Econ. 17 (2), 223–249.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56.
Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21, 785–818.
Barry, C.B., Brown, S.J., 1985. Differential information and security market equilibrium. J. Financ. Quant. Anal. 20 (4), 407–422.
Blankespoor, E., deHaan, E., Marinovic, I., 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: a review. J. Account. Econ. 70 (2–3), 101344.
Blankespoor, E., Dehaan, E., Wertz, J., Zhu, C., 2019. Why do individual investors disregard accounting information? The roles of information awareness and acquisition costs. J. Account. Res. 57 (1), 53–84.
Blankespoor, E., Miller, G.S., White, H.D., 2014. The role of dissemination in market liquidity: evidence from firms' use of Twitter. Account. Rev. 89 (1), 79–112.
Bourveau, T., Schoenfeld, J., 2017. Shareholder activism and voluntary disclosure. Rev. Account. Stud. 22 (3), 1307–1339.
Bowen, R.M., Dutta, S., Tang, S., Zhu, P., 2018. Inside the "black box" of private in-house meetings. Rev. Account. Stud. 23 (2), 487–527.
Bushee, B.J., Miller, G.S., 2012. Investor relations, firm visibility, and investor following. Account. Rev. 87 (3), 867–897.
Bushee, B.J., Jung, M.J., Miller, G.S., 2011. Conference presentations and the disclosure milieu. J. Account. Res. 49 (5), 1163–1192.
Chapman, K.L., Reiter, N., White, H.D., Williams, C.D., 2019. Information overload and disclosure smoothing. Rev. Account. Stud. 24 (4), 1486–1522.
Cheng, Q., Du, F., Wang, B.Y., Wang, X., 2019. Do corporate site visits impact stock prices? Contemp. Account. Res. 36 (1), 359–388.
Cheng, Q., Du, F., Wang, X., Wang, Y., 2016. Seeing is believing: analysts' corporate site visits. Rev. Account. Stud. 21 (4), 1245–1286.
Corwin, S.A., Schultz, P., 2012. A simple way to estimate bid-ask spreads from daily high and low prices. J. Finance 67 (2), 719–760.
Cui, Y., Che, W., Liu, T., Qin, B., Yang, Z., 2019. Pre-Training with Whole Word Masking for Chinese BERT arXiv preprint arXiv:1906.08101.
DeFond, M.L., Hung, M., Li, S., Li, Y., 2015. Does mandatory IFRS adoption affect crash risk? Account. Rev. 90 (1), 265–299.

Devlin, J., Chang, M.W., Lee, K., Toutanova, K., 2018. Bert: Pre-training of Deep Bidirectional Transformers for Language Understanding arXiv preprint arXiv:1810.04805.
Diamond, D.W., Verrecchia, R.E., 1991. Disclosure, liquidity, and the cost of capital. J. Finance 46 (4), 1325–1359.
Drake, M.S., Roulstone, D.T., Thornock, J.R., 2012. Investor information demand: evidence from Google searches around earnings announcements. J. Account. Res. 50 (4), 1001–1040.
Drake, M.S., Thornock, J.R., Twedt, B.J., 2017. The internet as an information intermediary. Rev. Account. Stud. 22 (2), 543–576.
Fernandes, N., Ferreira, M.A., 2009. Insider trading laws and stock price informativeness. Rev. Financ. Stud. 22, 1845–1887.
Ferris, S.P., Haugen, R.A., Makhija, A.K., 1988. Predicting contemporary volume with historic volume at differential price levels: evidence supporting the disposition effect. J. Finance 43 (3), 677–697.
Firth, M., Lin, C., Wong, S.M.L., Zhao, X., 2019. Hello, is anybody there? Corporate accessibility for outside shareholders as a signal of agency problems. Rev. Account. Stud. 24 (4), 1317–1358.
Frankel, R., Johnson, M., Skinner, D.J., 1999. An empirical examination of conference calls as a voluntary disclosure medium. J. Account. Res. 37 (1), 133–150.
Fung, S.Y.K., Raman, K.K., Zhu, X.K., 2017. Does the PCAOB international inspection program improve audit quality for non-US-listed foreign clients? J. Account. Econ. 64 (1), 15–36.
Glosten, L.R., Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Financ. Econ. 14 (1), 71–100.
Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36 (1–3), 337–386.
Huang, S., Lee, C., Song, Y., Xiang, H., 2022. A frog in every pan: information discreteness and the lead-lag returns puzzle. J. Financ. Econ. 145 (2), 83–102.
Jones, M.J., Shoemaker, P.A., 1994. Accounting narratives: a review of empirical studies of content and readability. J. Account. Lit. 13, 142.
Ke, B., Huddart, S., Petroni, K., 2003. What insiders know about future earnings and how they use it: evidence from insider trades. J. Account. Econ. 35 (3), 315–346.
Kerr, J., Sadka, G., Sadka, R., 2020. Illiquidity and price informativeness. Manag. Sci. 66 (1), 334–351.
Kirk, M.P., Markov, S., 2016. Come on over: analyst/investor days as a disclosure medium. Account. Rev. 91 (6), 1725–1750.
Kirk, M.P., Vincent, J.D., 2014. Professional investor relations within the firm. Account. Rev. 89 (4), 1421–1452.
Kyle, A.S., 1985. Continuous actions and insider trading. Econometrica 53 (6), 1315–1335.
Lawrence, A., 2013. Individual investors and financial disclosure. J. Account. Econ. 56 (1), 130–147.
Lee, C.M.C., Watts, E.M., 2021. Tick size tolls: can a trading slowdown improve earnings news discovery? Account. Rev. 96 (3), 373–401.
Leuz, C., Verrecchia, R.E., 2000. The economic consequences of increased disclosure. J. Account. Res. 91–124.
Leuz, C., 2018. Evidence-based policymaking: promise, challenges and opportunities for accounting and financial markets research. Account. Bus. Res. 48 (5), 582–608.
Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V., 2019. Roberta: A Robustly Optimized Bert Pretraining Approach arXiv preprint arXiv:1907.11692.
Maines, L.A., McDaniel, L.S., 2000. Effects of comprehensive-income characteristics on nonprofessional investors' judgments: the role of financial-statement presentation format. Account. Rev. 75 (2), 179–207.
Matsumoto, D., Pronk, M., Roelofsen, E., 2011. What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. Account. Rev. 86 (4), 1383–1414.
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. J. Finance 42 (3), 483–510.
Miller, B.P., 2010. The effects of reporting complexity on small and large investor trading. Account. Rev. 85 (6), 2107–2143.
Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22 (1), 435–480.
Roulstone, D.T., 2003. Analyst following and market liquidity. Contemp. Account. Res. 20 (3), 552–578.
Schoenfeld, J., 2017. The effect of voluntary disclosure on stock liquidity: new evidence from index funds. J. Account. Econ. 63 (1), 51–74.
Securities and Exchange Commission (SEC), 2009. Announcement from the SEC investor advisory committee. Available at: https://www.sec.gov/news/press/2009/2009-175.htm.
Siano, F., 2021. Contextualized News in Corporate Disclosures: A Neural Language Approach. Working paper. Boston University. October.
Siano, F., Wysocki, P., 2021. Transfer learning and textual analysis of accounting disclosures: applying big data methods to small(er) datasets. Account. Horiz. 35, 217–244.
So, E.C., Wang, R., Zhang, R., 2020. Meet markets: investor meetings and expected returns. Available at: SSRN 3751468.
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I., 2017. Attention is all you need. Adv. Neural Inf. Process. Syst. 30.
Welker, M., 1995. Disclosure policy, information asymmetry, and liquidity in equity markets. Contemp. Account. Res. 11 (2), 801–827.
Wu, Y., Lau, T., Atkin, D.J., Lin, C.A., 2011. A comparative study of online privacy regulations in the U.S. and China. Telecommun. Pol. 35, 603–616.

Lee is the Moghadam Family Professor, Emeritus, Stanford University, and the Hanson Professor of Accounting, Foster School of Business, University of Washington.

Zhong is an Associate Professor of Accounting in the School of Management at Fudan University.