Shall We Talk? The Role of Interactive Investor Platforms in Corporate Communication

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First Draft: August 21, 2020
Current Draft: September 19, 2021

Abstract: Between 2010 and 2017, Chinese investors used an online interactive platform to ask public companies around 2.5 million questions, the vast majority of which received a reply within two weeks. We analyze the contents of these investor interactive platform (IIP) dialogues using a natural language processing (NLP AI) algorithm, and present preliminary evidence on their causes and consequences. Our analyses show: (a) most questions reflect difficulties in processing information that is already in the public domain; (b) IIP activity is correlated with, but not subsumed by, other information events; and (c) controlling for other events, higher IIP engagement is associated with increases in trading volume, return volatility, market liquidity, and price informativeness for future earnings, as well as decreases in bid-ask spread. Financial statement related postings increase disproportionately around the adoption of new accounting standards, pointing to increased integration costs and providing direct support for the role of IIPs in facilitating information integration. Collectively, our results show investors face significant integration costs, but active firm engagement on IIPs helps reduce these costs, leading to improvements in the price formation process.

Keywords: *corporate disclosure, investor relations, information processing costs, interactive communication, market liquidity, price informativeness*

JEL Classification Codes: *M41, M45, G14, G15, G39*

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I. Introduction

Clear communication is generally achieved through a bidirectional process that involves *interactive exchange* between parties. In contrast, most corporate disclosure settings studied by academics emphasize supply-side issues. In these settings, the timing and content of corporate communiqués are primarily dictated by managerial priorities, 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 news, how these problems affect their trading decisions, and ultimately, how the information processing costs experienced by investors may impact the market price formation process.

In this study, we examine the causes and consequences of a new form of *interactive* corporate communication. Beginning in 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 (see Table 1 and 2). Between 2010 and 2017, Chinese investors posted around 2.5 million questions on these platforms. A vast majority of these questions (93.30% for Shenzhen-listed firms and 76.63% for Shanghai-listed firms) received a formal reply from company management, typically within a few days or weeks. By the last quarter of December 2017, over 99% of all Chinese listed companies were actively engaged in some amount of on-going dialogue with their investors through these platforms. Using website-extraction techniques, we collect a full set of interactive dialogues from these platforms for 1/2010 to 12/2017, with a view towards better understanding this phenomenon.

We view the rise of these investor interactive platforms (IIPs) in China as a significant development in corporate communications for three reasons. First, because these postings are driven by users of financial information rather than corporations, *the nature and content of the questions raised by investors* on these IIPs can provide important

new insights on the daily information needs of ordinary investors.[1] Second, 11 years after their introduction, these IIPs are now an integral part of the corporate communications landscape in China. Given their unique attributes (summarized in Section II) and widespread adoption, *it is important to understand how IIP activities affect investor trading behavior*, and whether these dialogues are incrementally important to investors after controlling for other firm-level information events. Finally, to the extent that IIPs are effective in reducing investor information costs, theory suggests firms participating actively on these IIPs may experience improvements in their price formation process. Therefore, we investigate *whether and how engagement on IIPs affects a firm's market liquidity and the informativeness of its stock price for future earnings*.[2] Our subsequent analyses are organized around the attainment of these three research goals.

With respect to the first goal, we are interested in understanding the types of problems investors encounter when using public information. Recent findings on investor information processing costs (e.g., Blankespoor, Dehaan, Wertz, and Zhu (2019; BDWZ) and Blankespoor, Dehaan, and Marinovic (2020; BDM)) suggest investors often need help to *integrate* (i.e., to understand and to act on) financial information that is already in the public domain.[3] At the same time, BDM acknowledges the difficulty in identifying these costs and parsing out their effect on investor behavior. In many respects, these Chinese IIPs are an excellent setting in which to study investor integration problems. Because participating firms on these IIPs are not allowed to use the platforms to disseminate of *new* information, most of the questions raised by

[1] We have no reason to believe the questioners are not "ordinary" or that they are particularly sophisticated. Nor do the postings appear to undergo significant vetting or filtering. Out of curiosity, we posted a small number of questions and in each case the question appeared as we asked it, and the company replied reasonably quickly.

[2] We use the terms "price informativeness" and "the informativeness of its stock price" interchangeably, to denote the extent to which current prices (or stock returns) capture information about a firm's future earnings. This usage is consistent with prior literature (see, for example, Lee and Watts, 2021, Drake, Roulstone, and Thornock, 2012, and Fernandes and Ferreira, 2009).

[3] Utilizing 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 observes 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."

investors involve problems encountered while trying to understand and act on previously disclosed information.

To analyze these questions, we first manually categorize a random subsample of 49,659 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 2,433,285 postings as to their *nature* and *content* (see Appendix B for details). Our results, presented in Table 3, show that a vast majority of these postings are looking for answers to or explanations for 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 their questions, the ten topics investor most frequently ask about, in descending order, are: company 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%).

Overall, consistent with BDWZ and BDM, our evidence suggests that investors face a wide range of integration problems when trying to understand and act on information that is already in the public domain. Most investors that post questions are looking for help in understanding company operations or interpreting corporate financial data. Sometimes the 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 economic events will be reflected in company reports. 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 make suggestions to management on how to handle various situations the company is facing (see Appendix A for examples of platform dialogue).

In the second stage of our analyses, we examine the effect of IIP activities on investor trading patterns. Specifically, we use a short-window research design to document the abnormal trading volume and abnormal absolute return associated with daily variations in the level of IIP activities (including number of questions and replies posted, as well

as the length of these questions and replies).[4] To distinguish IIP activities from other firm-related disclosures, we control for five other types of news releases coming from either the firm itself, or from sell-side analysts, or from the news media. Specifically, we control for: earnings announcements (*EA*), managerial earnings forecasts (*MEF*), other corporate announcements (*EVENTS*), sell-side analyst reports (*ANARP*), and firm mentions in the news media (*MEDIA*).

We find that these five types of firm-related disclosures have a positive association with IIP activities, but their collective ability to explain variations in daily IIP activities is limited. Statistically, investors are more likely to ask questions and firms are more likely to post replies on days with an information event, such as an earnings announcement. This result holds for each of the five traditional information events cited above (*EA*, *MEF*, *EVENTS*, *ANARP*, and *MEDIA*). However, taken together, these five information events explain less than one percent of the variation in the daily fluctuation in IIP activities. Clearly, most of the variation in IIP postings is not attributable to the information events commonly studied in prior literature.

Prior research suggests that integration problems can be an important reason why investors neglect publicly available information (BDWZ, 2019). Although new information is prohibited from being disclosed via the IIP, the two-way communication between managers and investors taking place on IIPs can nevertheless stimulate trading by reducing integration problems faced by investors. We examine this proposition by regressing two proxies for daily trading activity (abnormal volume and abnormal return volatility) on measures of daily IIP activity, controlling for five other information events and other potential drivers of abnormal trading.

Our results show that investors trade more actively when the daily level of IIP activity is higher (Table 5). Using abnormal trading volume as the dependent variable, we find

[4] In an earlier version of this paper, we focused on the effect of IIPs on firms' cost-of-capital using a longer-window (mainly annual) research design. The advantage of a short-window design is that it is easier to identify and isolate the effect that IIP activities have on investor behavior. The main disadvantage is that some important consequences of IIP engagement may not be captured by short-window market reactions. As noted by BDM, 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). On balance, we believe the approach adopted here is more powerful in detecting market outcomes and we thank the referee for suggesting it.

a positive and significant coefficient on each of the four IIP activity proxies (*Question Num., Question Length, Reply Num., and Reply Length*).[5] As expected, the estimated coefficients on the other five event indicators are also positive and strongly significant. This evidence suggests that controlling for other information events, higher IIP activity is associated with more active trading. We find similar results when the dependent variable is absolute abnormal return, as again all four IIP activity proxies are positive and strongly significant, even controlling for other events.

Overall, our results show that, controlling for other forms of corporate information events, higher IIP activities elicit a stronger reaction from market participants, as measured by both trading volume and return volatility. These findings are consistent with IIP activities serving as a source of information to investors. However, it is also possible that higher IIP activities simply attract investor attention, leading to higher noise trading (see, for example, Barber and Odean, 2008). We try to disentangle these possibilities through a third set of tests on firms' price formation process.

Theory indicates that when information processing costs are non-trivial, 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); and/or, (c) expand a firm's investor base, leading to lower costs of capital and improved market depth (Merton 1987). Our first set of tests showed that investors encounter many integration problems while attempting to act on public information. Our second set of tests find 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. Evidence that firms experience improvements in their price formation process would provide further support for the view that IIP activities are effective in mitigating investor integration costs.

[5] Each question (and each reply) has its own date and time stamp. Typically, the reply to a question is posted on a different (later) day from the original question. We define day t as the date of a posting (either a question or a reply). We compute *Question Num.* as the total of the questions posted on day t at a given firm's website. *Question Length* is the total number of words across all the questions for that day. We compute similar daily statistics for the replies, wherein the number (length) of replies for a given day t is the sum of the replies (total words) posted by a firm that day.

One channel through which IIP may improve firms' market liquidity is by reducing the information asymmetry between market participants. The market microstructure literature has long emphasized the effect of information asymmetry on security price formation and market liquidity (e.g., Kyle, 1985; Glosten and Milgrom, 1985). Uninformed investors "price protect" against adverse selection and this price protection is typically manifested 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 are effective in reducing information asymmetry costs, we should observe an improvement in market liquidity for firms that are more active on the platform.

We first examine the effect of interactive communication on daily bid-ask spreads, a common proxy for information asymmetry costs (Panel A in Table 6). The results show a significantly negative coefficient estimate on each of the four IIP variables, indicating that 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 II.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 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 by those investors that understand the question (and perhaps even partially anticipate the answer). Overall, the evidence here suggests increased daily IIP activities are associated with higher market liquidity, potentially due to lower information asymmetry risk.

Next, we conduct a second market liquidity test based on Amihud (2002) (Panel B in Table 6). In this specification, the variable of primary interest is the interaction term between daily IIP activities (*IIP*) and the RMB trading volume on that day (*Volume*). Our results show a significantly negative coefficient on this variable across all four measures of IIP activity, 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 IIP activity on the Amihud (2002) illiquidity measure (*AMIHUD*); and bid-ask spread (*SPREAD*), after controlling for the frequency of other firm-related disclosures over each firm-quarter. The results confirm that, at the quarterly level, a higher degree of interactive communication is associated with smaller Amihud illiquidity ratios and lower bid-ask spreads. 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 *AMIHUD* and *SPREAD*. These results show that firms that are active on IIPs experience significantly greater improvement in market liquidity over the treatment period than their propensity-score matched control firms.

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

To test this proposition, we conduct a quarterly forward earnings response coefficient (FERC) test. 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*). The main variable of interest is the coefficient on the interaction term between standardized unexpected earnings (*SUE*) and IIP activities (*IIP*). Our results show that the cumulative pre-EA return is more positively correlated with future *SUEs* when investors and managers are more actively engaged on the interactive platform. These findings are consistent with IIP activities effectively reducing investor information process 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. On July 2014, the Accounting Standards Board (ASB) of China formally revised five existing accounting standards and adopted three additional new standards (see Section IV.6 for details). We examine changes in IIP activities, particularly financial statement related questions and responses, in the quarter immediately after the implementation of these new standards.

Our results (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 deal 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, thus leading to an increase in both the number and the proportion of 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 the handling of publicly available information. These results also provide direct support for the view that IIPs are playing a useful role in facilitating information integration.

Taken together, our findings shed new light on the nature and importance of investor information processing costs. The BDWZ (2019) and BDM (2020) framework of information usage entails three sequential steps: awareness, acquisition, and integration.[6] Prior research has established the important role of awareness and acquisition costs. However, in the age of cyber news delivery, rumors, fake news, and information overload, integration costs may well be the primary impediment to

[6] 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.

investors when it comes to their ability to act judiciously on corporate information. Our results show that on a day-to-day basis, investors are concerned with a wide range of integration problems associated with publicly available information. We provide novel evidence on the specific types of issues investors wrestle with. We show that higher levels of IIP activities, both in terms of questions asked and replies received, are associated with increased trading volume and higher return volatility. More importantly, we show that increased IIP activities are associated with improvements firms' market liquidity and price informativeness, further supporting the view that IIPs can mitigate investor information processing costs.

These findings add to a growing stream of the disclosure literature that examines direct interactions between managers and capital market participants. Prior studies show such interactions may improve the informational efficiency of financial markets. However, these prior 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, and 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 publicly listed firms as well.

Our study is also related to a nascent but important literature that examines the determinants and consequences of Investor Relation, or IR, programs (Bushee and Miller 2012; Kirk and Vincent 2014). Prior 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 communication with investors through an online platform. Our results suggest that firms may benefit from incorporating some element of interactive dialogue into future IR programs.

We believe these findings should also be of interest to regulators concerned with reporting clarity and investor protection. Our results suggest that even "plainly-written" disclosures can cause confusion, and that interactive dialogue may play an important role in improving reporting clarity and investor comprehension. These results also speak to the SEC's expressed desire to "level the playing field" across

investor classes.[7] Current regulations aimed at mitigating discrimination across classes of investors focus mainly on increasing retail investor awareness of, and access to, firm disclosure. Our results suggest that a more important issue facing retail investors may be integration costs associated with information already in the public domain. To this end, our evidence suggests that efforts to reduce such costs, such as the introduction of IIPs, can benefit both retail investors and listed firms.

The remainder of this paper is organized as follows. In Section II we discuss our research motivation and provide further institutional background on these IIPs. Section III presents statistics on IIP adoption and usage, case studies, as well as a systematic analysis of investor posting. Section IV presents our main results on investor trading behavior and the market price formation process; and Section V concludes.

II. Research Motivation and Institutional Background

II.1 Investor Information Needs

Our first goal is to better understand the demand-side of corporate communications. Specifically, we wish to shed light on the informational issues investors face as they consider making investments in a company. Recent findings suggest investors do incur significant costs when processing information that is already available publicly (BDWZ 2019; BDM 2020). At the same time, these studies acknowledge that it is difficult to gain insights into the exact nature of these costs. A key motivation for this study is to assess the relative importance of information processing costs to investors and provide empirical evidence on the nature of their day-to-day information needs.

Prior research suggests such costs may be substantial. A large proportion of unsophisticated investors find financial disclosures are difficult to read (Jones and Shoemaker 1994). Small investors are also more likely to be affected by form vs. substance issues, due to limited processing capabilities and lack of financial expertise (Maines and McDaniel 2000). Miller (2010) finds small investors' processing and

[7] 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 benefits 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).

understanding of information is also impeded by reporting complexity. Conversely, concise and plainly written financial disclosure facilitates an individual's understanding of reported numbers (Lawrence 2013). Cyber news delivery may lead to information overload, which exacerbates the problem. Overloaded individuals rationally resort to information processing heuristics that can undercut information assimilation by the market (Chapman et al. 2019). Rumors and inaccuracies, spread through the blogs and investor forums, can also add complexity to the integration problem, hindering market price formation (Drake et al. 2017).

In short, prior work suggests that retail investors likely face significant costs when attempting to integrate publicly available information on listed firms. At the same time, these studies recognize it is difficult for researchers to gain insights into the nature of their informational difficulties. Our aim is to provide new, large-sample, evidence on the nature and content of investors' concerns when evaluating public firms.

II.2 Causes and Consequences of IIP Activity

Another goal of this study is to better understand the economic causes and consequences of interactive 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 make a modest contribution by documenting how IIP activities are related to five other information events from prior literature: earnings announcements (*EA*), managerial earnings forecasts (*MEF*), other corporate announcements (*EVENTS*), sell-side analyst reports (*ANARP*), and firm mentions in the news media (*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 conduct a comprehensive study of 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 intentions are to present a preliminary analysis that lays down a foundation for future, more detailed,

studies on the information content of these postings. With this in mind, we are focused sharply on understand two important issues: (a) whether more active participation on these platforms is associated an increase in investor trading activities (proxied by abnormal trading volume and return volatility), after controlling for other news events; and (b) whether IIP activities are associated with some measurable benefits to firms' price formation process (including market liquidity and price informativeness).

II.3 Interactive Platforms

In this subsection, we provide some institutional background on China's experiment in IIPs. According to the IIP websites, China's two major stock exchanges, SZSE and SHSE, each launched its platform with the expressed intent "to establish a direct bridge of communication between investors and listed firms." The SZSE platform, called Hu Dong 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 the platform. Investors can directly post their questions on the target firm's community page. Participating firms are required to appoint a high-leveled employee (a "Board Secretary") to oversee the replies made on its behalf. While the platform's operations are under the supervision of 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 exchanges to trace the identity of the questioner as needed. These monitoring mechanisms ensure some accountability in terms of what each side posts on the platform.

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 their 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.[8] As a result, the type of information that can be disclosed on these platforms is, by design, already in the public domain. From our perspective, this is helpful, as the interactive dialogues recorded on these platforms should provide a direct chronology of the types of problems investors encounter when processing information that is already publicly available.

To sum up, these IIPs are a novel development in corporate communications that is distinct from other disclosure venues in important ways. First, *their official status* as a sanctioned form of corporate communication 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*, so investors dictate the topics discussed. Third, *most questions are raised by ordinary investors* (as distinct from the Q&A sessions after a corporate conference call).[9] Fourth, *these IIPs do not disclose new information*, and are dedicated to explaining/amplifying prior disclosures. For these reasons, we believe an analysis of the activities on these platforms can provide unique insights into the information processing problems faced by investors.

III. 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. We begin data collection in January 2010,

[8] 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.*"

[9] The closest other forms of corporate communication are the Q&A segment of a corporate conference call (Matsumoto, Pronk, and Roelofsen 2011), and more recently, site visits to Shenzhen-listed companies (Bowen, Dutta, Tang, and Zhu 2018; Cheng, Du, Wang, and Wang 2019; So, Wang, and Zhang 2021). 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.

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 that have a presence on the platform. For each such firm, we then extract all the entire date-stamped history of questions and responses directly from each firm's community webpage.

III.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 exchanges (see Figure 1 for a graphic depiction). Clearly companies and investors quickly embraced these IIPs, and they are now an integral part of the investor communication rubric in China.

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 answers or 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 somewhat in subsequent years, as of 2017, each SZSE firm continues to receive around 40 questions per quarter from investors. This table also reports descriptive statistics on management response. Initially, investors needed to wait

about three weeks for a reply. As the platform ramped up, companies seem invest more into the IIP, and the speed of response increased. By the end of year 2013, even with sharply increased volume, investors were receiving replies on average within four calendar days. Since 2016, the average reply time settled to around 6 calendar days. We observe less intertemporal variation in management's response rate and in the length of their responses. In most quarters, management replied to 90% or more of the questions posted. In terms of the word count, each reply averaged 62 Chinese words in length.

Panel B in table 2 reports the platform activities for e Hu Dong, sponsored by the Shanghai 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 22.1 days, with a notable corresponding reduction in the most recent quarters. Column 3 shows that, for the entire sample period, the reply rate has been 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.

III.2 Case Studies

In Appendix A, we provide ten (translated) examples of the type of exchange that take place 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 are reasonably representative of the questions raised in these IIPs.

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 do not wish to, in one case) 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 (s)he is "too old" to look through 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 broadly public facts. Our reading is that management used this opportunity to ease concerns over potentially damaging news. In example #4, the 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 and asks why this was not disclosed. 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.

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.

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.

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 efforts. This type of question does not require any answer or explanation, and is usually responded to by a polite acknowledgement.

III.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 {5x19} matrix, according to the *nature* of the inquiry (5 categories) and the *content*, or subject matter, of the question (19 categories).[10] We then used the BERT model, a state-of-the-art Natural Language Processing AI algorithm, to conduct a more systematic analysis of the remaining 2,433,285 questions (98% of sample).

As explained in more detail in Appendix B, we constructed 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, these models generated the same classification as the 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%) are questions related to specific operating, financial, or investment issues etc. The second most comment type of posting are comments or suggestions to management (16.64%). This is followed by postings relate 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%).

[10] 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 there were differences in classification, these were discussed and the results reconciled.

Panel B groups these postings into 19 categories based on their *Content*, or subject matter. The ten topics investor most frequently ask about, in descending order, are: company 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 are asking for clarifications about the effect of economic events, other times they are simply unsure how certain transactions or events will impact the companies' financial reports. Broadly speaking, these questions are largely reflective of difficulties users encounter when trying to translate publicly available information into useful inputs in their investment process.

IV. Causes and Consequences of Platform Activity

IV.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 in prior literature. Corporate information disclosures are important environmental stimuli 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) *MEF* for a managerial earnings forecast; (5) *EVENTS* for some other corporate release (unrelated to earnings); (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 CSMAR or CNRDS database.

Panel A in Table 4 presents the pairwise Pearson correlations between these different information disclosure events. Not surprisingly, QUESTION and REPLY have a positive correlation of 0.372, suggesting these events frequently occur together. The other correlations are also positive but are of a lower 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 IIP activity (*Question Num., Question Length, Reply Num., and Reply Length*). A positively significant coefficient indicates that a traditional firm-related disclosure is positively related to IIP activity, while holding other information disclosures constant. However, the low adjusted R-squares (i.e., 0.003 in Columns 1-2 and 0.001 in Columns 3-4) show that variations in other firm-related disclosures only explain a small fraction of 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 QUESTION=1, and when REPLY=1. For example, in the total sample, 1.25% of total trading days contained an earnings announcement. Conditional on QUESTION=1, 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 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 vs unconditional likelihood of occurrence is quite small.

Taken together, Table 4 results shows that these five firm-related information events are positively associated with daily IIP activities, but their ability to explain variations in IIP activities is limited.

IV.2 IIP activities and investor trading behavior

Prior research suggests that integration problems can be an important reason why investors neglect publicly available information (BDWZ, 2019). Although new information is prohibited from being disclosed via the IIP, the two-way communication between managers and investors taking place on IIPs can nevertheless stimulate trading by reducing integration problems faced by investors. We examine this proposition by estimating the following equation using firm-day observations:

$$Trading_{i,t} = \alpha + \beta_1 IIP_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon_{i,t}\ , \quad (1)$$

where *Trading* is the investors' trading response for firm i on day t, as measured by either abnormal trading volume and or absolute abnormal returns. *IIP* is a measure of platform activity for firm i on day t. We use four proxies to measure platform engagement: (1) the number of questions posted each day (*Question Num.*), in the natural logarithm form; (2) the total number of words in the questions posted each day (*Question Length*), in the natural logarithm form; (3) the number of replies posted each day (*Reply Num.*), in the natural logarithm form; and (4) the number of words in the replies posted each day (*Reply Length*), in the natural logarithm form. 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: *EA, MEF, EVENTS, ANARP,* and *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 time fixed effects. Standard errors are clustered by firm to mitigate possible serial correlation in the error term (Petersen 2009).

Table 5 results show that investors trade more actively when the level of IIP activity is higher. The dependent variable in Panel A is 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, Haugen, and Makhija (1988) and Huang, Lee, Song, and Xiang (2021)). The coefficients on all four IIP activity measures are positive and significant at the 1% level, suggesting that investors trade more when the level of IIP activity is higher. Similar to IIP activity, other traditional information

events also have significantly positive association with abnormal trading volume.

The dependent variable in Panel B is absolute abnormal returns, defined as the residual from firm-by-firm regressions of daily stock return on the daily market return (similar to Ferris, Haugen, and Makhija (1988) and Ke, Huddart, and Petroni (2003)). We find that, as in Panel A, the level of IIP activity, both on the demand-side and on the supply-side, has a significant and positive correlation with daily 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.

Overall, our results show that, controlling for other forms of corporate information events, higher IIP activities elicit a stronger reaction from market participants, as measured by both trading volume and return volatility. 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 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 tests on firms' price formation process.

IV.3 Daily IIP activities and market liquidity

In this last set of 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 their price formation process would provide further support for the view that IIP activities are effective in mitigating investor integration costs.

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 trading behavior measures in Eq (1) with a measure of daily bid-ask spread (Corwin and Schultz, 2012). The results show a 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 following regression specification, inspired by the market liquidity measure in Amihud (2002):

$$ABRET_{i,t} = \alpha + \beta_1 IIP_{i,t} \times Volume_{i,t} + \beta_2 Volume_{i,t} + \beta_3 IIP_{i,t} + Other\ Disclosures + Controls + Fixed\ Effects + \varepsilon_{i,t}\ , \quad (2)$$

In this specification, the dependent variable is the daily absolute return (*ABRET*), and *IIP* is one of four measures of daily platform activity (*Question Num*; *Question Length*; *Reply Num*; or *Reply Length*). The variable of interest is the interaction term between daily IIP activities (*IIP*) and the RMB trading volume on that day (*Volume*). A negative coefficient on β_1 indicates that higher platform activity reduces the price impact of a given volume of trade and thus increases stock liquidity. All other variables are as defined in Eq. (1).

Panel B reports the results of estimating Eq. (2). Across all four measures of *IIP* activity, the coefficient on *IIP*×*Volume* is negative and significant at the 1% level. The consistently negative relation indicates that more active engagement on the interactive platform is associated with a lower price impact for any given level of trading volume. In other words, higher IIP activity is associated with an increase in the firm's market liquidity. The evidence here corroborates the results in Panel A, as both indicate higher IIP activities are associated with an improvement in market liquidity, potentially due to lower information asymmetry risk.

IV.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 the Amihud (2002) illiquidity measure (*AMIHUD*), measured as the ratio of the daily absolute return to the RMB trading volume on that day, averaged over the quarter; and bid-ask spread (*SPREAD*), after controlling for the

frequency of other firm-related disclosures over each firm-quarter.[11] For parsimony, we use a combined measure of platform activity (*IIP*) for these long-window test. To construct this combined measure, we standardize each individual measure of platform activity (i.e., the number of questions, question length, the number of replies, and reply length) and then compute *IIP* as the mean of these four standardized measures, with higher values representing greater platform activity.[12] The results in Panel A of Table 7 confirm that, at the quarterly level, a higher degree of interactive communication is associated with smaller Amihud illiquidity ratios and lower bid-ask spreads.

Although we find a positive relation between IIP activities and market liquidity, reliable causal inference 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 different-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,[13] 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 a PSM technique to identify a sample of matched control firms from the SHSE.[14] Following Fung, Raman, and Zhu (2017), we test for differences in the market liquidity measures between the treatment group and the

[11] 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; Subramaniam et al. 2016), including: firm size, financial leverage, market-to-book ratio, intangible asset, 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.

[12] The results are consistent if we use individual IIP measures instead.

[13] 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.

[14] To implement the PSM approach, we first estimate a logit regression where the dependent variable equals one if a firm is classified as treated and zero 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.

control group in the pre-adoption period and find the differences are not statistically significant, consistent with the pre-period parallel trend assumption. To conduct a difference-in-difference test, we estimate the following equation:

$$Mkt\_Liq = \propto + \beta \times TREAT \times POST + \gamma \times X + Firm\ Fixed\ Effects + Time\ Fixed\ Effects + \varepsilon \quad (3)$$

where *Mkt_Liq* is a measure of each firm's market illiquidity (either *AMIHUD* or *SPREAD*). *TREAT* is an indicator variable that takes the value of one for firms included in the treatment group, and zero otherwise. *POST* is an indicator for the post-event period which equals one when the year is 2011 or 2012, and zero otherwise. The major variable of interest is the interaction term between treatment group and the post-period (i.e., *TREAT*×*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-difference analysis. As shown, the coefficient on *TREAT*×*POST* is -0.0234 (t= -3.02) for the *AMIHUD* illiquidity measure and -0.0495 (t= -2.15) for the *SPREAD* measure. This DiD result further supports our earlier finding that direct interactive communication between managers and investors can significantly improve market liquidity.[15]

IV.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 – i.e., 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, Sadka, and Sadka, 2020). Specifically, when liquidity improves for a firm, information can be more readily incorporated into its stock price, thus increasing the informativeness of its stock price with respect to future

[15] Note that these DiD 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 DiD results are driven by SZSE firms that actively participated on the IIP.

fundamentals, such as reported earnings.

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

$$CAR_{i,t}^{[-60,-1]} = \beta_0 + \beta_1 SUE_{i,t} \times IIP_{i,t} + \beta_2 SUE_{i,t} + \beta_3 IIP_{i,t} + Other\ Disclosure + Controls + Fixed\ Effects + \varepsilon \ , \quad (4)$$

where the 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 (*CAR*). *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 (*SUE*) and IIP activities (*IIP*). A positive coefficient on β_1 indicates greater interactive communication between managers and investors is associated with an increase in the ability of pre-EA returns to predict future SUEs. As before, we use four proxies to measure platform engagement: *Question Num, Question Length*, *Reply Num,* and *Reply Length*, each measured at the quarterly level. Consistent with our short-window analyses, we control for other firm-related disclosures (*EVENTS*, *MEF*, *ANARP*, and *MEDIA*), 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 firm size (*SIZE*), market-to-book ratio (*MB*), asset growth (*GROWTH*) and return on assets (*ROA*). Finally, the regression also includes firm and time fixed effects, with standard errors corrected for clustering at the firm level.

Our results in Table 8 show that the cumulative pre-EA return is more positively correlated with future SUEs when investors and managers are more actively engaged on the interactive platform. This finding is robust and highly significant across all four measures of IIP activity (with t-statistics ranging from 6.23 to 7.75). 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 process costs, and thus accelerating the speed of price discovery associated with future

earnings.

IV.6 IIP activity after 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 (ASB) of China formally revised five existing accounting standards and adopted three additional new standards.[16] We examine the effect of this major change in reporting standards on IIP activities by estimating the following regression:

$$FS\_IIP_{i,t} = \alpha + \beta_1 AS\ Change_{i,t} + +Other\ Disclosure + Controls + Fixed\ Effects + \varepsilon \quad , \tag{5}$$

where the dependent variable, *FS_IIP,* is a measure of financial statement related IIP activities measured over days t to t+30 relative to each quarter t's EA. We use four different proxies for *FS_IIP*, corresponding to: (1) the number of financial statement related questions (*FS Question 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 Question 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 one for 2014 Q3 observations, and zero otherwise. As before, we control for other forms of firm-

[16] 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.

related disclosures and variables that prior studies (e.g., Frankel 1999; Drake et al. 2012; Bourveau and Schoenfeld 2017) suggest may affect corporate disclosure. Firm and Year & 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 deal 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, thus leading to an increase in both the number and the proportion of financial statement related questions. In addition, the evidences also lend the support for the important role of interactive communication in facilitate the information integration.

V. Conclusion

This study presents an analysis of the causes and consequences of a new form of interactive corporate communication. Between 2010 and 2017, a vast majority of Chinese publicly listed firms began using an online platform to engage their investors in direct dialogue. We examine the nature and content of these exchanges and link the 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 in the public domain; (b) controlling for other firm-related information events, higher platform activities are associated with greater trading volume and return volatility, and (c) higher platform activity is also associated with improvements in market liquidity and price informativeness. Collectively, our results suggest that this new form of interactive dialogue can potentially reduce investor information costs and improve corporate communications, resulting in measurable benefits to firms' price formation process.

An important caveat to note 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 in the absence of such monitoring.

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 that IIP activities have on investor behavior and market metrics. Because we have millions of individual IIP events, these short-window tests also have exceptional 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 towards evidence-based policymaking, wherein policy decisions are made on the basis of best available scientific and empirical evidence (Leuz 2018). The aforementioned caveat notwithstanding, our findings suggest interactive communication platforms are an important development in investor communications, one that could potentially lead to new ways to improve reporting clarity, protect retail investors, and improve the quality of equity markets.

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Appendix A: Examples of Platform Dialogue

In this appendix, we present several 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 questions commonly observed on the IIPs.

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

科陆电子 [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 [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 ID300014]

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 [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 [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 [601908]

Questions: In my opinion, your company has good prospects. Meanwhile, I would like to give your company some advices: 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 B.1 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 that 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.

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.

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

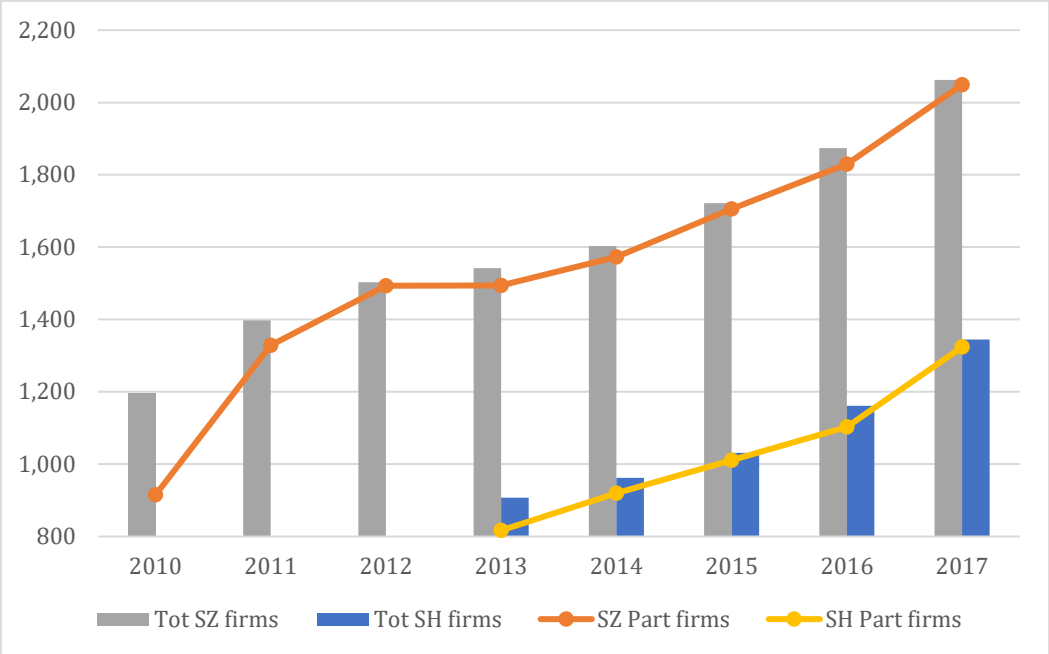
[18] Dynamic masking: BERT relies on randomly masking and predicting words in the sentence. The original BERT implementation performed masking once during data preprocessing, resulting in a single static mask. To avoid using the same mask for each training instance in every epoch, RoBERTa duplicates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

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

	SZ Stock Exchange			SH Stock Exchange			Total		
year	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.

Figure 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.

Table 2. Quarter-by-quarter IIP activities

Panel A. Shenzhen Stock Exchange (SZSE)

Year-Quarter	Question Num.	Answer 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**

Table 2. Quarter-by-quarter IIP activities (continued)

Panel B. Shanghai Stock Exchange (SHSE)

Year-Quarter	Question Num.	Answer 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 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.

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

Panel A. 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. 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.

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

	Question Num.	Question Length	Reply Num.	Reply Length
	(1)	(2)	(3)	(4)
EA	0.0446***	0.1742***	0.0196***	0.0804***
	(12.16)	(12.56)	(6.23)	(7.49)
EVENTS	0.0444***	0.1719***	0.0388***	0.1329***
	(17.72)	(18.49)	(19.31)	(19.76)
MEF	0.0843***	0.3247***	0.0540***	0.1794***
	(12.39)	(12.92)	(8.77)	(8.74)
ANARP	0.0911***	0.3575***	0.0483***	0.1568***
	(16.00)	(17.28)	(11.91)	(11.67)
MEDIA	0.0604***	0.2163***	0.0322***	0.0833***
	(4.92)	(4.97)	(4.17)	(3.68)
Constant	0.2531***	1.0768***	0.1885***	0.7171***
	(65.14)	(72.76)	(64.91)	(71.48)
Observations	3752191	3752191	3752191	3752191
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 other corporate releases not related to earnings (*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 (*Question Num.*), in the natural logarithm form; (2) the number of words in question per day (*Question Length*), in the natural logarithm form; (3) the number of replies per day (*Reply Num.*), in the natural logarithm form; (4) the number of words in reply 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).

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)
Question Num.	***0.0035****			
	(25.41)			
Question Length		***0.0008****		
		(25.67)		
Reply Num.			***0.0020****	
			(22.06)	
Reply Length				***0.0005****
				(22.31)
EA	0.0025***	0.0026***	0.0027***	0.0027***
	(20.22)	(20.52)	(21.94)	(21.96)
EVENTS	0.0027***	0.0027***	0.0027***	0.0027***
	(40.46)	(40.55)	(40.77)	(40.78)
MEF	0.0031***	0.0031***	0.0033***	0.0033***
	(13.14)	(13.23)	(13.70)	(13.76)
ANARP	0.0041***	0.0041***	0.0041***	0.0041***
	(33.33)	(33.35)	(33.69)	(33.67)
MEDIA	0.0089***	0.0089***	0.0090***	0.0090***
	(33.04)	(33.01)	(33.07)	(33.08)
MV	-0.0038***	-0.0038***	-0.0038***	-0.0038***
	(-10.73)	(-10.66)	(-10.60)	(-10.57)
MB	0.0002***	0.0002***	0.0002***	0.0002***
	(3.42)	(3.40)	(3.30)	(3.29)
Constant	0.0818***	0.0814***	0.0816***	0.0814***
	(10.48)	(10.41)	(10.42)	(10.39)
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3751687	3751687	3751687	3751687
Adjusted R^2	0.049	0.048	0.047	0.046

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

Panel B. Daily Absolute Abnormal Return

	Dependent Variable=Absolute Abnormal Return			
	(1)	(2)	(3)	(4)
Question Num.	***0.0005****			
	(12.74)			
Question Length		***0.0001****		
		(12.41)		
Reply Num.			***0.0002****	
			(8.08)	
Reply Length				***0.0001****
				(8.64)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3751687	3751687	3751687	3751687
Adjusted R^2	0.140	0.140	0.140	0.140

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, Haugen, and Makhija (1988) and Huang, Lee, Song, and Xiang (2021)). The dependent variable in Panel B is daily absolute abnormal return, defined as the residual from firm-by-firm regressions of daily stock return on the daily market return (similar to Ferris, Haugen, and Makhija (1988) and Ke, Huddart, and Petroni (2003)).

For both panels, key variables of interest in Columns 1-4 respectively are: (1) the number of questions per day (*Question Num.*), in the natural logarithm form; (2) the number of words in question per day (*Question Length*), in the natural logarithm form; (3) the number of replies per day (*Reply Num.*), in the natural logarithm form; (4) the number of words in reply 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 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*). In addition, 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 time fixed effects. 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 6. IIP activity and market liquidity

Panel A. Daily Bid-ask Spread

	Dependent Variable=Bid-ask Spread			
	(1)	(2)	(3)	(4)
Question Num.	***-0.0280****			
	(-13.13)			
Question Length		***-0.0063****		
		(-12.69)		
Reply Num.			***-0.0059****	
			(-3.42)	
Reply Length				***-0.0014****
				(-2.97)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3721260	3721260	3721260	3721260
Adjusted R^2	0.146	0.146	0.146	0.146

Panel B. The Price Impact of Trading Volume

	Dependent Variable=Daily Absolute Return			
	(1)	(2)	(3)	(4)
Question Num.×Volume	***-0.0051****			
	(-14.28)			
Question Length×Volume		***-0.0013****		
		(-12.63)		
Reply Num.×Volume			***-0.0019****	
			(-8.21)	
Reply Length×Volume				***-0.0004****
				(-5.74)
Volume	0.0301***	0.0301***	0.0284***	0.0283***
	(67.07)	(66.49)	(66.19)	(65.74)
Question Num.	0.0012***			
	(18.95)			
Question Length		0.0003***		
		(16.76)		
Reply Num.			0.0005***	
			(10.09)	
Reply Length				0.0001***
				(8.41)
Other Disclosures	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3751687	3751687	3751687	3751687
Adjusted R^2	0.402	0.402	0.401	0.401

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 daily absolute return. The variable of interest is the interaction term between daily IIP activities and the RMB trading volume on that day (*Volume*). In the spirit of Amihud (2002), this coefficient would be negative if higher activity on the IIP reduces the price impact of trading volume.

For both panels, the platform activity measures in Columns 1-4 respectively are: (1) the number of questions per day (*Question Num.*), in the natural logarithm form; (2) the number of words in question per day (*Question Length*), in the natural logarithm form; (3) the number of replies per day (*Reply Num.*), in the natural logarithm form; (4) the number of words in reply 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 time fixed effects. 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

	AMIHUD	SPREAD
	(1)	(2)
IIP	***-0.0022****	***-0.0105****
	(-4.43)	***(-5.77)***
Other Disclosures	YES	YES
Controls	YES	YES
Firm FE	YES	YES
Time FE	YES	YES
Observations	64478	64478
Adjusted R^2	0.387	0.577

Panel B. Difference-In-Difference Analysis

	AMIHUD	SPREAD
	(1)	(2)
TREAT×POST	***-0.0234****	***-0.0495****
	(-3.02)	***(-2.15)***
Other Disclosures	YES	YES
Controls	YES	YES
Firm FE	YES	YES
Time FE	YES	YES
Observations	12480	12480
Adjusted R^2	0.678	0.574

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 Amihud (2002) illiquidity measure (*AMIHUD*) in model 1, and bid-ask spread (SPREAD) in model 2. The Amihud (2002) illiquidity measure is defined as the average ratio of the daily absolute return to the RMB trading volume; and bid-ask spread is an estimator from daily high and low prices developed by Corwin and Schultz (2012).

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 one for firms included in the treatment group (defined as actively engaged firms on the Shenzhen stock exchange), and zero otherwise. *POST* is an indicator for post-event period, equal to one if it is year 2011 or year 2012, and zero if it is year 2008 or year 2009. Standard errors are calculated using clustering at the firm level. T-statistics are presented in parentheses. **, *** indicates statistical significance at the 5% and 1% level, respectively (two-tailed).

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

	Dependent Variable=$CAR^{[-60,-1]}$			
	(1)	(2)	(3)	(4)
Question Num. ×SUE	***0.2346****			
	(7.75)			
Question Length×SUE		***0.0956****		
		(7.00)		
Reply Num. ×SUE			***0.2058****	
			(7.16)	
Reply Length×SUE				***0.0756****
				(6.23)
SUE	0.1584**	0.1279*	0.2631***	0.2723***
	(2.57)	(1.84)	(4.83)	(4.75)
Question Num.	-0.0050***			
	(-6.20)			
Question Length		-0.0014***		
		(-4.05)		
Reply Num.			-0.0039***	
			(-5.29)	
Reply Length				-0.0010***
				(-3.20)
EVENTS	0.0016**	0.0016*	0.0016*	0.0016*
	(2.01)	(1.95)	(1.96)	(1.92)
MEF	0.0073**	0.0070**	0.0072**	0.0070**
	(2.58)	(2.46)	(2.54)	(2.45)
ANAREPORT	0.0115***	0.0114***	0.0114***	0.0114***
	(15.14)	(15.07)	(15.10)	(15.06)
MEDIA	0.0222***	0.0220***	0.0220***	0.0219***
	(15.91)	(15.76)	(15.78)	(15.68)
SIZE	0.0315***	0.0315***	0.0315***	0.0316***
	(11.18)	(11.14)	(11.17)	(11.15)
MB	0.0058***	0.0059***	0.0059***	0.0059***
	(13.76)	(13.84)	(13.77)	(13.85)
GROWTH	-0.0268***	-0.0263***	-0.0270***	-0.0266***
	(-4.90)	(-4.79)	(-4.93)	(-4.86)
ROA	-0.0454	-0.0392	-0.0439	-0.0363
	(-0.75)	(-0.65)	(-0.72)	(-0.60)
Constant	-0.7924***	-0.7913***	-0.7945***	-0.7950***
	(-12.60)	(-12.55)	(-12.61)	(-12.58)
Firm FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	52346	52346	52346	52346
Adjusted R^2	0.080	0.079	0.080	0.079

This table presents results from the analyses of the effect of IIP activities on the market response to upcoming earnings announcements, based on firm-quarter observations between 2010 and 2017, inclusively. Specifically, we estimate:

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

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 (EA). 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 EA (*Question Num.*), in the natural logarithm form; (2) the number of words in question over days t-60 to t-1 relative to each quarter t's EA (*Question Length*), in the natural logarithm form; (3) the number of replies over days t-60 to t-1 relative to each quarter t's EA (*Reply Num.*), in the natural logarithm form; (4) the number of words in reply over days t-60 to t-1 relative to each quarter t's EA (*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 EA (*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 EA (*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 EA (*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 EA (*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*). 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).

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

	FS Question Num.	FS Reply Num.	FS Question 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)
ANAREPORT	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 (ASB) 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 EA (*FS Question 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 EA (*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 EA (*FS Question 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 EA (*FS Reply Proportion*).

Our variable of primary interest (*AS Change*) is equal to one for 2014 Q3 observations, and zero 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's EA (*EVENTS*) , in the natural logarithm form; (2) the number of managerial earnings

forecasts over days t to t+30 relative to each quarter's EA (*MEF*), in the natural logarithm form; (3) the number of analyst reports over days t to t+30 relative to each quarter t's EA (*ANAREPORT*), 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 EA (*MEDIA*), in the natural logarithm form. 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).