Seeing is Believing: Analysts' Corporate Site Visits*

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ABSTRACT

This study examines the impact of site visits on analysts' forecast accuracy based on a sample of analysts' corporate site visits to Chinese listed firms during 2009-2012. Using a difference-in-differences approach, we find that analysts who conduct site visits ("visiting analysts") have a greater increase in forecast accuracy than non-visiting analysts. Consistent with the notion that site visits facilitate analysts' information acquisition through observing firms' operations, we find that the results are stronger for manufacturing firms, for firms with more tangible assets, and for firms with more concentrated business lines. In addition, we find that the effect of a site visit is greater when the site visit is an analyst-only visit, when the current site visit is preceded by fewer site visits, and when visiting analysts are located far from the visited firms. Moreover, visiting analysts' forecast revisions are accompanied by a higher market response. Furthermore, we find that site visits partially mitigate non-local analysts' information disadvantage. Lastly, our determinant analysis shows that the likelihood of analysts' site visits increases with the expected benefits and decreases with the costs adherent to conducting site visits. Collectively, these results indicate that corporate site visits are an important information acquisition activity for analysts.

Keywords: Site visits, analyst forecasts, information acquisition activities, local advantage.

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1 Introduction

The usefulness of analyst research arises from analysts' skill in processing public information and their active information acquisition activities (e.g., Healy and Palepu 2001; Ivkovic and Jegadeesh 2004; Asquith, Mikhail, and Au 2005). Prior research extensively examines how analysts use financial statement information to generate earnings forecasts and whether they are efficient in doing so (Bradshaw 2011). Although prior research infers that analysts rely on their information acquisition activities (e.g., Chen, Cheng, and Lo 2010), direct evidence is limited. Bradshaw (2011) and Brown, Call, Clement, and Sharp (2015) call for research to better understand analysts' information acquisition activities. The primary hurdle is the lack of data on such activities, which are largely private (Soltes 2014). This study fills the void by investigating whether financial analysts obtain useful information to improve the accuracy of their earnings forecasts through a specific type of information acquisition activity: corporate site visits.

The prevalence and importance of site visits are evident from the surveys conducted in both the U.S. (Brown et al. 2015) and Europe (the 2012 All-Europe Research Team Survey). However, in the U.S. and Europe, firms either do not maintain archival records of site visits or prohibit the distribution of such information. This study exploits the recent regulation of the mandatory disclosure of site visits in China. The Shenzhen Stock Exchange (SZSE) requires listed firms to disclose the information related to investors' site visits in their annual reports starting from 2009. This mandatory disclosure requirement provides a unique setting for testing how analysts benefit from their corporate site visits. The Chinese setting has another advantage. Listed firms in emerging markets such as China operate in an opaque information environment (Morck, Yeung, and Yu 2000). Site visits are thus expected to be a relatively more important information source, complementing public disclosures in the markets, compared with well-developed markets. Therefore, examining site visits in China increases the power of the tests in determining the effect of analysts' site visits on their forecast performance.

Based on prior research and in-depth interviews with investor relations (IR) managers, sell-side analysts, and fund managers, we expect that analysts can improve their earnings forecast accuracy through corporate site visits. In a typical site visit, the visiting analysts engage in face-to-face talks with IR managers and divisional managers, and then take a tour of the firm's operating and production activities.[1] The face-to-face talks can help analysts to gain additional details about, and insights into, a firm's performance. Observing a firm's operations and facilities, such as its factories and business units, allows an analyst to better understand its production process, corporate culture, and employee morale, potentially leading to an improvement in her forecast accuracy. However, the information obtained from site visits might not be material enough to affect analysts' forecasts of current year's earnings. Indeed, based on the data of 75 private interactions between analysts and top executives of one large U.S. firm, Soltes (2014) finds no evidence that analysts' forecast accuracy improves after these private interactions. Thus, it is an empirical question whether analysts can improve their forecast accuracy through corporate site visits.

We adopt a difference-in-differences research design to evaluate the effect of site visits on analysts' forecast accuracy. We calculate the forecast accuracy changes around site visits and then compare the changes between visiting and non-visiting analysts. Our sample consists of 6,651 site visits to 931 unique firms during 2009-2012. Consistent with our hypothesis, we find

[1] According to the corporate site visit policies disclosed by listed firms, IR managers, including board secretaries and securities affairs representatives, are usually the liaisons for site visits. They are responsible for approving site visit applications, organizing field tours, and accompanying the visitors during the site visits. Our interviews suggest that the practice is consistent with these corporate policies.

that visiting analysts experience an improvement in forecast accuracy after site visits compared to non-visiting analysts. Using alternative approaches to demonstrate the usefulness of site visits, we find that the market reaction is greater for the forecast revisions issued by visiting analysts than those by non-visiting analysts.

One salient feature of site visits is that analysts can observe a firm's operations and facilities. In contrast, analysts' other information acquisition activities, such as hosting investor conferences and attending conference calls, are mainly in the form of interacting with top executives (Mayew, Sharp, and Venkatachalam 2013; Green, Jame, Markov, and Subasi 2014a). Consistent with the importance of observing firms' operations, we document a greater effect of site visits to firms in the manufacturing industries, to firms with higher asset tangibility, and to firms with more concentrated business lines. Such results highlight the notion that the information channels in site visits are different from those in investor conferences, which are shown to be more useful for firms with more *intangible* assets (Green et al. 2014a).

We next explore the richness of the site visit data, particularly the disclosure of visitors' names. We find that the effect of site visits on analyst forecast accuracy is more pronounced for the site visits conducted by sell-side analysts only than those conducted jointly by sell-side analysts and buy-side investors. This finding suggests that analyst-only site visits are more likely to be information acquisition activities, while analysts' site visits along with buy-side investors are, to some extent, client service events, as suggested by Soltes (2014). Moreover, we find that the effect of site visits is more pronounced for site visits with fewer preceding site visits and for site visits conducted by analysts located far from the visited firms, where the visiting analysts are less informed prior to the visits.

Unlike other types of analysts' activities, analysts are less likely to interact with top executives during site visits. As shown in Cheng, Du, Wang, and Wang (2015), a firm's top executives participate in only 15.2% of the site visits.[2] Moreover, if site visits are merely a reflection of visiting analysts' close relationship with top managers, the effect of site visits would be stronger for analysts located nearby the firm, whereas the geographic proximity facilitates the establishment of private relationship with top executives.[3] However, we find that non-local analysts benefit more from site visits than local analysts. Furthermore, one might argue that the analysts who have better access to management are more likely to conduct site visits and issue more accurate forecasts. In one additional analysis, we exclude the analysts who issued strong buy recommendations or had investment banking relationship with the visited firm. Our inferences remain the same. We also conduct a series of analyses and find that our results are unlikely to be driven by managers' selective disclosure during site visits.

Another alternative explanation for our results is that capable and well-informed analysts choose to conduct site visits and they also issue more accurate forecasts. We do not believe that this alternative argument can explain our results because the difference-in-differences research design, to a large extent, controls for the potential self-selection issue. Nevertheless, we perform two additional analyses to further address this issue. First, we find that visiting and non-visiting analysts have similar forecast accuracy in the pre-visit period, inconsistent with the notion that visiting analysts are more skilled or better informed. Second, for every site visit to a firm, we restrict the non-visiting benchmark group to the analysts who have visited this firm at other times. The inferences remain the same. It is, however, possible that analysts' time-varying access to the

[2] Cheng et al. (2015) hand collect the information about firm executives' participation in site visits from the detailed records of 4,425 site visits from the SZSE website in 2013. Please note that it is only in 2013 that firms started to provide the detailed minutes of site visits, including whom the visitors meet with during site visits. Such information is not available in our sample period.

[3] Prior studies (e.g., Bae, Stulz, and Tan 2008) provide evidence consistent with the argument that analysts are more likely to have access to top executives of the firms located in the same area.

information and analysts' additional research in preparation for site visits, at least partly, drive the results.

Moreover, we use two alternative research designs to examine the improvement in analysts' forecast accuracy after site visits. First, we compare the relative accuracy of forecasts issued by an analyst for firms she visits and for firms she does not visit in the same year. Second, we compare the relative accuracy of the forecasts issued for the same firm by an analyst between the years when she conducts site visits and the years when she does not. For both tests, we hold analyst characteristics constant, and in the second test we further hold firm characteristics constant. We find that earnings forecasts after site visits are more accurate than other earnings forecasts issues by the same analysts. These results mitigate the concern that our results are driven by omitted analyst- or firm-characteristics.

We then link our analyses to the literature on geographic advantage of analysts by investigating whether non-local analysts can overcome their information disadvantage through site visits. We first confirm that on average local analysts have higher forecast accuracy than non-local analysts. However, the forecasts issued by non-local analysts who conduct one site visit are as accurate as those issued by local analysts who do not conduct any site visit. If non-local analysts visit a firm twice or more, their forecasts are more accurate than those issued by non-visiting local analysts.

Lastly, because not all analysts conduct site visits, we conduct a determinant analysis to investigate what factors affect analysts' site visit decision. We find that analysts are less likely to visit firms that are geographically far away, but are more likely to visit firms with more tangible assets and firms with more concentrated business lines. Analysts from larger brokers are more likely to conduct site visits than other analysts. These results indicate that the likelihood of analysts' site visits increases with the expected benefits and decreases with the costs adherent to conducting site visits.

Our study contributes to the financial analyst research by enhancing our understanding of analysts' information discovery role and by providing direct evidence on the link between analysts' information acquisition activities and their forecast performance. A large body of literature explores the factors associated with better forecast performance, including industry specialization, firm-specific experience, geographic proximity, and educational ties.[4] These studies focus more on analysts' attributes – who they are, and less on what they do (Bradshaw 2011). Analysts' information acquisition activities are confidential in nature and the challenge of directly observing and measuring their effects has hindered researchers' ability to understand their role in analysts' forecast performance. We circumvent this issue by relying on a new regulation in China that requires firms to disclose information on analysts' site visits.

Our study builds on and extends an emerging literature that directly examines analysts' activities. For example, Mayew et al. (2013) focus on analysts who ask questions during conference calls and conclude that these analysts have superior private information prior to conference calls. Green et al. (2014a, 2014b) focus on analysts hosting investor conferences and conclude that these analysts have superior access to management. Using private data from one NYSE-listed company, Soltes (2014) examines analysts' private interactions with managers (largely through phone calls) and finds that analysts' forecast accuracy does not improve afterward. Compared with these activities, site visits represent analysts' proactive information acquisition and are featured by analysts' observing firms' operation and assets, rather than relying only on the discussions with top executives. We show that site visits have a greater effect

[4] Please see Jacob, Lys, and Neale (1999), Mikhail, Walther, and Willis (1997), Malloy (2005), and Cohen, Frazzini, and Malloy (2010) for examples.

for firms whose operation is of higher observability. Moreover, thanks to the richness of the data, we are able to explore how the usefulness of site visits varies with the characteristics of site visits and the visited firms. Such variations help explain why the effect of site visits to one firm, as documented in Soltes (2014), might not be generalizable to other firms. Our in-depth field interviews also contribute to our understanding of the complex process of analysts' corporate site visits.

Our study also contributes to the literature on local information advantage. Malloy (2005) and later studies (e.g., Bae et al. 2008) show that local analysts issue more accurate forecasts than remote analysts. Our results indicate that site visits help non-local analysts to mitigate the information disadvantage to a certain extent.

The findings in the Chinese context are important in their own right given China's increasingly important role in the world economy and the rapid development of its financial service industry. Our results should provide suggestive evidence on the role of site visits in the U.S. capital markets. Anecdotes of investors' site visits abound in the U.S., especially in the post-Regulation FD period, during which selective disclosure is banned and investors must rely more on other means to obtain information (Call, Chen, and Tong 2013; Soltes 2014).[5] However, we acknowledge the possibility that the institutional differences between China and the U.S. might limit the generalizability of our findings.[6]

The remainder of this paper proceeds as follows. Section 2 reviews the related literature and develops hypotheses. Section 3 describes the sample and research design. Section 4 reports

[5] Prior research also examines other types of selective access events, such as investors' private meetings with firm executives (Solomon and Soltes 2015).

[6] We would like to point out that China has adopted the U.S. version of Regulation FD by mandating that if an issuer discloses material nonpublic information to certain enumerated persons, it must make public disclosure of that information. According to the Article 41 of the CSRC's Regulation FD, which took effective on January 31, 2007, "A listed company shall, hold conference calls, analysts' meetings, road shows, accepting investors' field investigation, etc., to communicate with the institutions and individuals about the business operations, financial status and other events, but it shall not provide any inside information."

the main analyses and Section 5 additional analyses. Section 6 concludes the paper.

2 Prior literature, institutional background, and hypothesis development

2.1 Analysts' information acquisition and forecast performance

Analysts are important capital market intermediaries who help decrease the information asymmetry between managers and outside investors (e.g., O'Brien and Bhushan 1990). Their superior forecast performance generally arises from their active information acquisition and superior information processing skills. Prior studies examine how analysts' forecast performance varies with industry specialization (Jacob et al. 1999), firm-specific experience (Mikhail et al. 1997), and brokerage firm size (Clement 1999; Jacob et al. 1999), among other factors. However, it is not well understood how analysts' information acquisition activities influence their forecast performance. Recent studies find that analysts who ask questions during conference calls (Mayew et al. 2013) or host investor conferences (Green et al. 2014a, 2014b) have superior information. However, it is unclear whether their superior performance is driven by the activities per se or by self-selection, as skilled or better-connected analysts are more likely to ask questions and host conferences.

In determining the direct effect of an information acquisition activity, ideally the activity should benefit the analysts who participate, but not others. This is not the case for investor conferences or conference calls, as non-hosting analysts can also attend investor conferences and silent analysts can also participate in conference calls and benefit from such activities. In contrast, corporate site visits meet this requirement. Corporate site visits exclusively benefit the analysts who visit the firm (i.e., visiting analysts). Non-visiting analysts have no direct access to the information obtained during site visits. Therefore, one can compare visiting and non-visiting analysts' forecast accuracy to determine the direct effect of site visits.

2.2 Corporate site visits and visiting analysts' information advantage

2.2.1 Institutional background and the main hypothesis

Site visits refer to the visits investors pay to firms in order to talk to managers and other employees, and to observe the firms' production activities and operation facilities. To understand how, when, and why analysts conduct site visits, we study the related regulations, corporate policies, and corporate disclosures on site visits. We also conduct in-depth interviews with three IR managers, three sell-side analysts, and three fund managers.[7] We include some of the quotes below whenever appropriate. We use the insights gained from these materials and field interviews to enrich our understanding of the institutional background, to substantiate our hypothesis development, and to interpret our empirical results in a broader context.

Site visits are not restricted to a few favored market participants according to the "Guidelines of Investor Relations Management" (referred to as Guidelines hereafter). In Article 41 of the Guidelines, the SZSE states that "Listed companies should try to accommodate the request from investors, analysts, and fund managers to visit company headquarters and project sites to the greatest extent." In the Guidelines, the SZSE emphasizes that "Listed companies should arrange the site visits properly so that visitors may better understand the companies' business and operational situations." According to our interviewees, firms usually do not reject site visit requests unless the requested visit occurs in a blackout or sensitive period (e.g., before major announcements). Whether analysts can visit firms on their preferred dates depends on the negotiation between the firm and the analysts. For example, one interviewed analyst noted that, "Companies usually do not say no to site visit requests, but whether you can have your preferred

[7] We follow a strict interview protocol, asking the same set of open-ended questions in the same order across all interviews.

visit time depends on your relative status and long-term relationship with the company."

Most site visits are initiated by sell-side analysts. Analysts can go by themselves or along with their buy-side clients, depending on whether the visit is mainly an information-acquisition or client-service activity. A typical site visit starts with a company briefing and a Q&A session, followed by a tour of the firm's factories and operation facilities. During the site visits, analysts engage in face-to-face talks with IR managers and/or other mid-level managers and observe the operation process. As one interviewed IR manager and one interviewed analyst described,

> "A typical site visit lasts for three to four hours—one to two hours of talk, followed by a two-hour visit to our real-estate development site."

> "Companies are very flexible in accommodating our interview requests. For example, if we have a really good discussion session in the morning, and ask to visit the production assembly lines in the afternoon, companies do not reject such a request."

These interactions help analysts to triangulate their model parameters, obtain more detailed and contextual information about public announcements, and better understand the firm's future strategy and positioning. The interviewed analysts confirmed that site visits could help them gain both earnings and non-earnings related information, such as the contextual factors that are filtered out in managers' announcements due to the constraint of the standardized presentation format required by the regulators, the strategic positioning of a certain business unit and a product, and other soft information such as the firm's relationship with local government and banks. For example, one interviewed analyst described the information obtained from corporate site visits as follows:

> "Most of the discussions focus on two parts: the operational situation and future prospects. For the current operational situation, analysts usually ask about the production, sales, pricing, market competition, and future expected changes in prices and margins. This is relevant to our financial modeling forecasts. We can adjust the model parameters based on the information obtained from the site visit. For the future prospects, we want to hear about the management team's strategic planning and their positioning of a certain business sector and product line."

In summary, these discussions imply that analysts can improve their forecast accuracy through site visits.[8] Our first hypothesis is thus stated as follows (in alternative form):

H1: Ceteris paribus, the forecast accuracy of visiting analysts improves after corporate site visits.

However, the information obtained from site visits may not be material enough to affect analysts' forecasts of the current year's earnings. It is also possible that analysts rely too much on the information conveyed by IR managers or employees and do not actively discover new information by themselves. If a firm intends to hide information, visiting analysts will obtain few informative cues. Moreover, visitors usually do not meet with top executives such as CEOs and CFOs during site visits.[9] According to some studies (e.g., Bushee, Jung, and Miller 2013), top executives are usually the main sources of information; thus analysts might not be able to obtain useful information from corporate site visits. These discussions imply that whether visiting analysts' forecast accuracy improves after site visits is an empirical question.

2.2.2 Cross-sectional variation

The effectiveness of site visits may vary with the expected benefits from observing the production process and facilities, the purpose of the visits, and the quality of the information environment faced by the visiting analysts prior to their visits.

Compared with analysts' other activities, site visits are featured by the opportunities to observe the production process, operating assets, factory assembly lines, and employee morale.

[8] In this paper, we focus on forecast accuracy because it is the most frequently studied performance metric of analysts in the accounting literature. The information obtained from site visits likely affects forecast accuracy more than other performance metrics, such as recommendation profitability. Analysts also have incentives to improve their forecast accuracy. In China, analysts' compensation is largely determined by their annual ranking in performance, evaluated by some news media such as *New Fortune* and *Today Investment*. While *New Fortune's* star analyst ranking is largely based on the votes of institutional investors, *Today Investment's* star analyst ranking is more objective, and one of the awards is explicitly designated for the best analysts with the most accurate earnings forecasts in every industry.
[9] As discussed in Cheng et al. (2015), a firm's top executives participate in only 15.2% of the site visits.

We thus expect that the effectiveness of site visits varies with the informativeness of these visual cues obtained from such observation. First, we predict that the visual cues are more informative for manufacturing firms and firms with more tangible assets because these firms have more observable production activities and assets. These predictions are also consistent with analysts' belief. For example, one interviewed analyst noted that "We feel that the observation part of site visits is very important when we visit manufacturing firms or firms with more tangible assets."

Second, a site visit is more effective if the observed visual cues provide insights into the firm's overall performance to a greater extent. The more concentrated a firm's business lines, the larger the extent to which the on-site operation represents its overall business, and hence the more useful the site visits are for visiting analysts to forecast the firm's operating performance.

The above discussions lead to the following hypothesis (in alternative form):

H2: Ceteris paribus, the improvement in visiting analysts' forecast accuracy, as stated in H1, is more pronounced for manufacturing firms, firms with more tangible assets, and firms with more concentrated business lines.

Site visits may serve purposes other than information acquisition. As noted by one interviewed analyst, "It serves different purposes when analysts go by themselves versus when they invite their buy-side clients along with them. The former do so to look for information and potential opportunities, and the latter do so to provide buy-side services." Prior research also indicates that when sell-side analysts conduct site visits with buy-side investors, the primary purpose of the visits is to help buy-side clients to gain corporate access (Brown et al. 2015; Soltes 2014). Therefore, we expect site visits to have a greater effect on the improvement in forecast accuracy when conducted by sell-side analysts only.

The effectiveness of site visits should also vary with the information environment faced by visitors prior to the visits. First, prior research finds that non-local analysts have significant information disadvantage due to the lack of alternative informal channels and local contact (Malloy 2005; Bae et al. 2008). This is consistent with our field insights as noted by one analyst, "Although local analysts do visit local companies more often, they may have alternative private information channels and do not need to rely on site visits as much as non-local analysts." We thus expect non-local analysts to improve more from conducting site visits compared with local analysts. Second, a site visit that is preceded by other investors' site visits may be less informative, as visitors in those preceding visits might have already conveyed the same information to the market. Such an argument is consistent with the belief of some analysts, as summarized by one interviewed analyst: "If the information has already been revealed by a first mover, the effect of a follow-up report is rather limited." It thus follows that the visitors benefit more from their site visits if there are fewer site visits prior to theirs.

The above discussions lead to our third hypothesis (in alternative form):

H3: Ceteris paribus, the improvement in visiting analysts' forecast accuracy, as stated in H1, is more pronounced for analyst-only site visits, for non-local analysts, and for site visits with fewer preceding visits .

3 Sample and methodology

3.1 Sample

The data on analysts' corporate site visits to firms listed on the Shenzhen Stock Exchange (SZSE) are available from 2009 onward. According to the SZSE Information Fair Disclosure Guidelines, effective from August 2006, firms listed on the SZSE must report to the China Securities Regulatory Committee (CSRC) two working days before site visits. The firm must submit a summary of the site visit to both the CSRC and SZSE after such a visit is conducted. However, these reports are not available to the general public. In 2008 the SZSE implemented a new disclosure rule mandating that all listed firms disclose the summary information about every site visit in their annual reports starting from 2009.[10] The disclosure of site visits is strictly enforced. The SZSE publicly denounces firms that fail to disclose site visit information.

Appendix A provides an example of site visit records showing that investors conduct site visits to a firm's headquarters, operation facilities, and warehouses. The list of site visit records occasionally includes non-site-visit events such as telephone interviews, performance illustration webinars, email exchanges, non-deal road shows, investor conferences, industry summits and forums, and annual broker conferences. We exclude such non-site-visit events from our sample. An analyst on average conducts one site visit per year to the firms she follows, although some analysts conduct more. As shown in Appendix A, the analyst from GF Securities visited the firm on April 12 and again on December 15, 2011.

We hand-collect the site visit records from the annual reports of the SZSE-listed firms during 2009-2012. Our data include the event dates and the names of the visiting institutions. Table 1 presents the sample selection procedures. First, we only include the site visits involving at least one sell-side Chinese broker.[11] We drop the site visits where there are no analyst earnings forecast data from the CSMAR database for the visited firms in the current year.[12] Second, some site visits fall on adjacent dates and we combine them as one site visit event to avoid misclassifying visiting analysts as non-visiting analysts. Third, we require that at least one

[10] Analysts likely have other non-official means to obtain information on their peers' site visits. First, occasionally there are voluntary disclosures on some firms' websites about the site visits. But it is unclear how timely or comprehensive such disclosures are. Second, based on the authors' conversations with the analysts who have conducted corporate site visits, some analysts may get to know such information from experts' network (e.g., their friends in other brokers covering the same industry) or through their peers' research reports issued after site visits.

[11] We identify sell-side brokers based on the following process: First, we assign one unique broker ID to each broker, even when they take different formats in different firms' site visit records (e.g., "CITIC Securities," "CITIC Securities Company," and "CITIC Securities Co. Ltd.,") or when they change names over the sample period. Second, we exclude the buy-side analysts' visits based on a manual check of the brokers' websites. This process leads to a total of 167 unique brokers, 114 of which are Chinese brokers and 53 of which are foreign brokers. Of the 114 Chinese brokers, 102 brokers' forecasts are covered in the CSMAR database.

[12] We match the brokers' names in the analyst forecast database with those in the site visit database. Because one broker usually has only one analyst covering a specific firm, we use "broker" and "analyst" interchangeably when discussing forecasts.

earnings forecast is issued by visiting analysts during the period from six months before the site visit to the end of the first month afterward. This requirement is necessary to test the change in an analyst's forecast accuracy after a site visit. We impose the same requirement for the non-visiting analysts. Lastly, we exclude financial firms or firms that have missing values for control variables in the regressions.

The final sample includes 6,651 site visits to 931 unique firms between 2009 and 2012. Of these site visits, 526 occurred in 2009, 1,323 in 2010, 1,719 in 2011, and 3,083 in 2012. The increase in the number of site visits over time is largely driven by the increase in the number of firms with site visits, from 159 in 2009 to 765 in 2012, which is consistent with the gradual increase in the number of listed firms in the SZSE. The number of visits per firm fluctuates over the sample period (3.31 in 2009, 4.41 in 2010, 4.21 in 2011, and 4.03 in 2012).

In our final sample, the mean (median) number of site visits conducted by the same visiting analysts to the same firm in a single year is 1.29 (1.00). Relatedly, we find that 91% of the brokers (i.e., their analysts) covered in the CSMAR database visited at least one SZSE firm during the sample period.

3.2 Research design

To evaluate the effect of site visits, we adopt a difference-in-differences research design by comparing the change in forecast accuracy between visiting and non-visiting analysts. We rely on the visitors' names to identify the visiting analysts – the analysts from the brokers whose names are listed for a particular site visit. We refer to the analysts who follow the same firms but whose brokers' names are not associated with the site visits as non-visiting analysts.[13] While there is only one visiting analyst for most site visits, for about 23% of site visits there are

[13] We also require that for each site visit event, non-visiting analysts do not conduct any other site visit to the same firm during the period beginning from six months before to the end of the first month afterward. This constraint is imposed to ensure a clean sample of non-visiting analysts as the benchmark group for such a visit.

multiple visiting analysts. In addition, for every site visit, there are many non-visiting analysts, whose forecasts serve as the benchmark for that of visiting analysts. To increase the power of the test and to avoid the inflation of statistical tests, the unit of analysis is analyst group by site visit. Specifically, we calculate forecast accuracy for each analyst group (visiting or non-visiting analyst group) based on the group's consensus forecast in the pre-visit period (i.e., six months before the site visit) and post-visit period (i.e., one month after the site visit). The change in forecast accuracy for an analyst group controls for the effects of analyst-specific characteristics. The difference in the change in forecast accuracy between visiting and non-visiting analyst groups controls for the effects of potential concurrent events or firm characteristics that can affect analysts' performance. As such, the difference-in-differences approach captures the effects of corporate site visits on visiting analysts' forecast accuracy.

3.2.1 Regression model for H1

We use the following regression to investigate the improvement in visiting analysts' forecast accuracy:

$$\begin{aligned} \Delta Accuracy_{k,j,t} = {} & \alpha + \beta Visit_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} \\ & + \gamma_4 ANA\_group_{k,j,t} + \gamma_5 MV_{j,t} + \gamma_6 NI\_std_{j,t} + \gamma_7 Inst\_holding_{j,t} + \gamma_8 Indep_{j,t} \\ & + \gamma_9 BM_{j,t} + \gamma_{10} Growth_{j,t} + \gamma_{11} Loss_{j,t} + \gamma_{12} BHAR_{j,t} + Industry_{j,t} \\ & + \varepsilon_{k,j,t}, \end{aligned} \qquad (1)$$

where $\Delta Accuracy_{k,j,t} = -(Post\_Visit\_AFE_{k,j,t} - Pre\_Visit\_AFE_{k,j,t})$. This variable captures the change in forecast accuracy for analyst group *k* (visiting or non-visiting analyst group) from the pre- to the post-visit period for the site visit occurring on day *t* for firm *j*; a positive value indicates an improvement in forecast accuracy. Because the unit of analysis is site visit-analyst group, we have two observations for each site visit, one for the visiting analyst group and the other for the non-visiting analyst group. For each analyst group, we calculate the forecast error (*Pre_Visit_AFE*) in the pre-visit period based on the mean of individual analysts' most recent annual EPS forecasts (i.e., group consensus forecast) in the pre-visit period. Forecast error is calculated as the absolute value of the difference between the group consensus forecast and actual EPS, scaled by the stock price at the beginning of the year and expressed in percentage.[14] The forecast error in the post-visit period (*Post_Visit_AFE*) is calculated in the same fashion based on the first forecast issued by each analyst in the group in the post-visit period. If a visiting (or non-visiting) analyst does not update her forecast during the post-visit period, we assume the post-visit forecasts to be the same as the pre-visit forecast.[15] The main variable of interest is the indicator variable for visiting analysts ($Visit_{k,j,t}$). The coefficient on this variable captures the improvement in visiting analysts' forecast accuracy relative to that of non-visiting analysts. H1 implies that $Visit_{k,j,t}$ has a positive coefficient.

Following prior studies, we control for other variables that affect analysts' forecast accuracy. Forecasts issued closer to earnings announcements are more accurate than older forecasts (Clement 1999). Thus, we control for the change in forecasting horizon (*ΔHorizon*), which is measured as the natural logarithm of the difference in the mean of the forecasting horizon (the number of days) of individual earnings forecasts for each analyst group from the pre- to post-visit periods. In addition, because more experienced analysts make more accurate earnings forecasts (Mikhail et al. 1997), we control for analysts' firm-specific experience (*Firmexp*), which is measured as the natural logarithm of the average number of years the analysts have been following the firm. Prior literature shows that analysts' forecast accuracy is affected by the size of their brokerage firms, with larger brokers having more resources. Thus,

[14] In China, forecast errors, when scaled by stock prices, are usually very small. This is due to the very high PE ratio in Chinese stock markets. Our statistics are comparable to those reported in other studies of Chinese financial analysts, such as Gu, Li, and Yang (2013). In an untabulated additional analysis, we use the relative forecast accuracy score as developed in Hong and Kubik (2003) and our inferences remain the same.

[15] The inferences remain the same when we exclude these analysts from the analyses. Separately, some analysts issue a post-visit forecast but not a pre-visit forecast. For these cases, we assume that the pre-visit forecast to be the same as the mean value of all other analysts' pre-visit forecasts. The inferences remain the same if we exclude these analysts from the analyses.

we control for brokerage firm size (*Brokersize*), which is measured as the number of unique financial analysts working for the broker during the year. As suggested by prior literature, the consensus forecast of a larger group of analysts is more accurate. Thus, we control for group size (*ANA_group*), which is measured as the number of analysts in the group. We calculate the above variables separately for the visiting and non-visiting analyst groups.

Lastly, we control for the firm characteristics that can affect the analysts' forecast accuracy, including institutional ownership (*Inst_holding*), board independence (*Indep*), firm size (*MV*), book-to-market ratio (*BM*), buy-and-hold abnormal returns (*BHAR*), earnings volatility (*NI_std*), sales growth (*Growth*), and a loss firm indicator (*Loss*). Appendix B provides the definitions of these variables. We also include industry fixed effects in the regression model. The t-values are based on standard errors adjusted for firm and year level clustering.

3.2.2 Regression models for H2 and H3

To test H2, we expand Equation (1) by adding the interaction terms between the indicator for visiting analysts and the firm characteristics capturing the effectiveness of on-site observation:

$$\Delta Accuracy_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Firm\_char_{j,t} + \beta_3 Visit_{k,j,t} \times Firm\_char_{j,t} + \boldsymbol{\gamma Controls} + \varepsilon_{k,j,t}, \qquad (2)$$

where *Firm_char* refers to one of the three indicator variables for manufacturing firms, firms with high asset tangibility, and firms with high business concentration, respectively. H2 implies that the coefficient on the interaction term is positive.

H3 predicts that the effect of a site visit depends on whether it serves the purposes of buy-side client service or information acquisition, whether the visiting analysts are non-local analysts, and whether there are fewer preceding visits. Note that these partitions are only relevant for the visiting analysts. Therefore, to test H3, we add to Equation (1) only the interaction term of *Visit* and the indicator for the partition without adding the standalone variables:[16]

$$\Delta Accuracy_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Visit_{k,j,t} \times Visit\_char_{k,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{k,j,t}, \qquad (3)$$

where *Visit_char* is an indicator variable that equals one separately for visiting analyst observations when site visits involve sell-side analysts only, when site visits are dominated by non-local analysts, and when site visits are preceded with fewer site visits; it is equal to zero for other visiting analyst observations and for all of the non-visiting analyst observations. Appendix B provides detailed definitions of these indicator variables. H3 implies that the coefficient on the interaction term is positive.

4 Empirical results

4.1 Univariate tests

Table 2 presents the descriptive statistics on forecast accuracy. As shown in the table, visiting and non-visiting analysts have similar forecast accuracy in the pre-site-visit period. However, in the post-site-visit period, the visiting analysts have significantly lower forecast errors (1.077 vs. 1.201 with p-value=0.01) and therefore higher forecast accuracy than the non-visiting analysts. As a result, the visiting analysts experience a much more pronounced improvement in forecast accuracy (0.164 vs. 0.041 with p-value = 0.00), consistent with H1.

Table 2 also reports the descriptive statistics on other variables for our main analyses. Recall that for each site visit event, analyst-specific characteristics are different for visiting and non-visiting analyst groups, but the firm-specific characteristics are the same for both groups. Therefore, we present the descriptive statistics for the analyst-related variables separately for the

[16] The objective of H3 is to test whether the usefulness of site visits varies with the characteristics of site visits or visiting analyst groups, and they are not relevant for non-visiting analysts. When we include the main effect of these variables in an untabulated analysis, the inferences remain the same. Also while we include the interaction terms separately in the regression, the results are quantitatively similar when we include all interaction terms in the same regression model (untabulated).

two subsamples. We observe that visiting analysts have a smaller change in forecast horizon (*ΔHorizon*), have slightly more firm-specific experience on average, and are more likely to work for larger brokers than non-visiting analysts. The average number of analysts is only 1.385 for the visiting analyst group but 7.234 for the non-visiting group. This notable difference in group size indicates that financial analysts usually do not cluster in one specific site visit when scheduling their visits to a firm.

As for the firm characteristics, the average market value is RMB10.3 billion (around US$1.6 billion), the average institutional ownership is 44%, the average book-to-market ratio is 0.360, and the average sales growth is 28%. Most firms have board independence lower than 40%. More than half of the sample firms have board independence equal to exactly 33% because of the CSRC's regulatory requirement that at least one-third of board directors be independent. Consistent with the general listed firm population, only 1% of the visited firms are loss firms. Lastly, the sample firms have skewed buy-and-hold market-adjusted annual returns, with a mean of 15% but a median of 1%.

4.2 Multivariate test for H1

Table 3 reports the multivariate regression results for H1. Consistent with the univariate analysis, we find that visiting analysts experience a larger improvement in their forecast accuracy compared with non-visiting analysts. The coefficient on *Visit* is significantly positive at the 0.01 level (coefficient = 0.1292 with t = 5.13). This effect is also economically significant. The magnitude of the coefficient on *Visit* implies a relative improvement in forecast accuracy of about 10% based on the mean pre-visit forecast error of the visiting or non-visiting analyst groups (1.24, as presented in Table 2). This result is consistent with H1 that analysts obtain useful information for earnings forecasts during their site visits.[17] This result is also consistent with analysts' belief, as stated by one interviewed analyst, that "Site visits are the most important information channel for sell-side analysts to acquire information. I spend two-thirds of my working time on the road visiting companies."

In terms of control variables, we find that the coefficient on *ΔHorizon* is significantly positive, implying that the post-visit forecasts are more accurate than the pre-visit forecasts, which have a longer horizon. Analysts from larger brokerage firms and those who cover larger firms experience a smaller improvement, likely because they are more informed in the pre-visit period. In comparison, we find that analysts experience a larger improvement in forecast accuracy for firms with higher earnings volatility, firms with higher book-to-market ratios, and loss firms.

In summary, visiting analysts experience a larger improvement in forecast accuracy than non-visiting analysts after controlling for other potential determinants. This finding implies that analysts obtain information from site visits that is useful for their earnings forecasts.

4.3 Cross-sectional analyses for H2

Table 4 reports the results from the test of H2. We construct indicator variables for manufacturing firms (*Manufacture*), for firms with a higher level of tangible assets (*Tangibility*), and for firms with more concentrated business lines (*Concentration*). Based on the CSRC's industry classification, 66.1% of site visits are paid to manufacturing firms, as shown in Table 2. *Tangibility* equals 1 when the ratio of PP&E over total assets is greater than the sample median, and 0 otherwise. The average PP&E/total assets is 0.23. To capture a firm's business concentration, we use the Herfindahl-Hirschman index (HHI) of a firm's segment sales. The

[17] Our interview suggests that the site visits that occur in the month after quarterly earnings announcements or the initial announcements of mergers & acquisitions are likely to be initiated by the firms, rather than by the analysts. Our conclusions still hold after excluding these site visits.

average HHI is 0.604. *Concentration* equals 1 when the HHI of segment sales is greater than the sample median, and 0 otherwise.

As shown in Columns (1) to (3) of Table 4, the coefficients on the interaction terms, *Visit×Manufacture, Visit×Tangibility,* and *Visit×Concentration*, are positive and significant at the 0.05 level or better (t = 2.08, 2.30, and 2.81, respectively). These results are consistent with H2 that analysts experience a larger improvement in forecast accuracy when they conduct site visits to manufacturing firms, to firms with more tangible assets, and to firms with more concentrated business.

4.4 Cross-sectional analyses for H3

To test H3, we construct an indicator for site visits that are conducted by sell-side analysts only (*AnalystOnly*), which equals 1 for analyst-only visiting groups, and 0 for visiting groups involving non-analyst visitors (typically buy-side investors). Table 2 shows that 37% of the site visits are analyst-only visits. Column (1) of Table 5 presents the regression results. We find a positive coefficient on *Visit×AnalystOnly* (t = 7.07), suggesting that site visits are more effective in improving forecast accuracy when they are conducted by analysts only. This finding is consistent with the notion that sell-side analysts often accompany their clients during corporate site visits as their client service trips rather than as trips for information acquisition, as noted by one of the interviewed fund managers: “Sell-side analysts have quotas to organize site visit tours, which are viewed as part of their services.”

To test the incremental effect of site visits for non-local visiting analysts, we construct an indicator for site visits dominated by non-local visiting analysts (*Remote*) (i.e., visits in which non-local visiting analysts outnumber local visiting analysts in attendance). Non-local analysts refer to the analysts whose brokerage firms are located more than 400 kilometers away from the visited firm's headquarters. As shown in Table 2, for 72.7% of the site visits, the visiting analysts consist mainly of non-local analysts. Column (2) of Table 5 presents the regression results. Consistent with the prediction, we find a positive coefficient on *Visit×Remote* (t = 9.90).

Similarly, to test the incremental effect of site visits with fewer preceding visits, we construct an indicator variable (*Unpreceded*) for site visits with fewer than the median number of site visits conducted in the preceding month. As reported in Table 2, on average there are about 1.7 site visits conducted in the month before the current site visit. Column (3) of Table 5 presents the regression results. We find a positive coefficient on *Visit×Unpreceded* (t = 2.84).

In sum, consistent with H3, site visits are more effective in improving forecast accuracy when they are conducted by analysts only and by analysts who are located farther away from the visited firms, and when they are preceded by fewer site visits.

5 Additional analyses

5.1 An alternative explanation – self-selection of visiting analysts

It is possible that skilled analysts are more likely to conduct site visits and they also produce more accurate forecasts, leading to a positive association between site visits and forecast accuracy. Another possibility is that analysts choose to visit the firms that they are more familiar with and hence they produce more accurate forecasts based on their superior prior knowledge about this firm. If these alternative explanations are valid, we should expect that visiting analysts have more accurate earnings forecasts than non-visiting analysts in the pre-visit period. However, as reported in Table 2, the forecast accuracy of visiting analysts is similar to that of non-visiting analysts in the pre-visit period. To ensure that the univariate results are not driven by confounding factors, we also conduct a multivariate analysis of the *level* of forecast accuracy in the pre-visit period. As reported in Column (1) of Table 6, we find that there is no significant difference in forecast accuracy between visiting and non-visiting analysts in the pre-visit period; the coefficient on the site visit indicator variable (*Visit*) is insignificant at conventional levels (t = -0.35).

In contrast, when we examine the post-visit level of forecast accuracy, we find that forecast accuracy is higher for visiting analysts than for non-visiting analysts, as reported in Column (2) of Table 6. The coefficient on *Visit* is significantly positive (t = 3.07). Therefore, the relative improvement in visiting analysts' forecast accuracy is driven by their more accurate post-visit forecasts. This is further supported by the regression results reported in Column (3), where we include both pre- and post-visit observations and add to the regression the post-visit indicator (*Post*) and its interaction with *Visit*. We find that the coefficient on *Visit* is still insignificant (t=-0.24), but that on *Visit*×*Post* is significantly positive (t = 5.67). Such a finding suggests that visiting analysts have similar forecast accuracy as non-visiting analysts before the site visit; however, after the site visit they show greater forecast accuracy than non-visiting analysts.

To further address the self-selection issue, we impose additional requirement on the benchmark group. Specifically, for each firm we exclude the non-visiting analysts who did not conduct any site visit to the firm over the sample period. As such, the reduced non-visiting analyst group only consists of the analysts who visit the firm at other times. This additional data requirement ensures that visiting and non-visiting analysts more comparable in terms of conducting site visits to the same firm; they just visit the firm at a different time. Column (1) of Table 7 presents the regression results for this sample. The coefficient on *Visit* remains significantly positive (t = 6.94), suggesting that the improvement in visiting analysts' forecast accuracy is due to the information obtained from site visits, not due to their choice of conducting site visits.

In the same vein, it is possible that analysts with better access to managers are more likely to conduct site visits and are more capable of acquiring information during site visits. To address this concern, we exclude the analysts who issue strong-buy recommendations in the year prior to site visits and those analysts who have investment banking relationship with the firm in the past, the analysts who presumably have better access to managers. The regression results for this sample are reported in Column (2) of Table 7. Our inferences remain the same: the coefficient on *Visit* is significantly positive (t = 5.67).

In summary, these additional analyses indicate that our results are not driven by the alternative explanations based on the self-selection of visiting analysts.

5.2 An alternative explanation – Selective disclosure

It is unclear whether the benefits of site visits come from analysts putting together an information mosaic, as discussed above, or from managers' selective disclosure during analysts' site visits. While selective disclosure is clandestine to detect, we identify two cases where selective disclosure is more likely to occur and then examine whether our results are stronger in these cases. First, we expect that selective disclosure is more likely to occur during site visits to the firms that violated disclosure rules and later were investigated by the regulators. Second, we expect that analysts with favorable relationship with the firm are more likely to visit the firm regularly and selective disclosure is more likely to occur during their visits. However, in untabulated analyses, we find that site visits in these cases are not more useful than others. That is, we fail to find any evidence consistent with the alternative explanation based on selective disclosure.[18] Despite these results, we would like to note that selective disclosure is hard to

[18] To the extent that selective disclosure is more likely to occur during the visits of the analysts who have favorable opinions towards the firm, the robust results after excluding the site visits conducted by the analysts who have issued

detect by nature and we leave it to future research to investigate to what extent the benefits we document are driven by managers' selective disclosure.

5.3 Alternative research design - Comparison based on the same-analyst observations

Our analyses above are based on the comparison between visiting and non-visiting analysts. We use the difference-in-differences design to address potential omitted analyst characteristics. To further address the concern that some unobservable factors might affect visiting and non-visiting analysts differently, we use the observations from the same visiting analysts and conduct two tests to examine whether analyst forecast accuracy experiences an improvement after site visits. In the first test, we compare the relative accuracy of earnings forecasts issued for firms visited by an analyst versus that for firms not visited by the same analyst in the same year. If site visits are useful in improving forecast accuracy, the relative forecast accuracy should be higher for the former than for the latter. In the second test, we focus on analyst-firm pairs and compare the relative forecast accuracy in the years when an analyst visits the firm versus in the years when she does not visit the same firm. Again, if site visits are useful in improving forecast accuracy, the relative forecast accuracy should be higher in the former than in the latter.

Under the alternative research design, the unit of analysis is analyst-firm-year. As in Bae et al. (2008), we calculate the relative forecast accuracy measure (*Rel_Accuracy*) as follows:

$$Rel\_Accuracy_{i,j,t} = (-1) \times \frac{AFE_{i,j,t} - Avg\_AFE_{j,t}}{Avg\_AFE_{j,t}},$$

where $AFE_{i,j,t}$ is the forecast error of analyst i for firm j in year t. For each analyst, we calculate forecast error using the analyst's most recent annual earnings forecast issued in the year before the firm's earnings announcement. $Avg\_AFE_{j,t}$ is the mean forecast error of all analysts who cover firm j in fiscal year t. A positive value of *Rel_Accuracy* indicates that the forecast error of

strong-buy recommendations recently for the firm or by those with investment banking relationship with the firm, as reported in Column (2) of Table 7, also suggest that selective disclosure is not driving our results.

analyst i for firm j in year t is smaller than the average forecast error for firm j in year t. We then estimate the following regression to test whether site visits are useful in improving forecast accuracy:

$$Rel\_Accuracy_{i,j,t} = \alpha + \beta Visit\_Freq_{i,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{i,j,t} \qquad (4)$$

We define the count variable $Visit\_freq_{i,j,t}$ as 2 (1, 0) if analyst i visits firm j two or more (one, zero) times in the six-month period before the issuance date of the most recent earnings forecast, or in the period between last year's earnings announcement date and the issuance date of the most recent earnings forecast, whichever is longer.[19]

Table 8 reports the regression results, Column (1) for the comparison across firms followed by the same analyst within the same year, and Column (2) for the comparison across years within the same analyst-firm pair. As reported in the table, the coefficient on *Visit_freq* is significantly positive in both columns (t = 10.63 and 4.36, respectively). These results suggest that analysts' earnings forecasts for a firm are more accurate when analysts visit this firm than their forecasts for the firms that they do not visit in the same year, or than their forecasts for the same firm but in the years they do not visit it. Overall, these analyses indicate that our inferences are not driven by the unobservable analyst or firm characteristics.

5.4 Investors' response to visiting analysts' forecast revisions after site visits

Visiting analysts usually disclose in their reports that their earnings forecasts and recommendations are based on the recent site visits.[20] To the extent that investors are aware of the usefulness of analysts' site visits, we expect that conducting site visits increases the

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[19] Due to the data requirement for calculating *Visit_freq* (i.e., information related to site visit frequencies in the past six months), the sample of earnings forecasts includes those with forecasting dates of July 2009 onward.

[20] Based on a sample of 250 randomly selected analyst reports that were issued by the visiting analysts in the month after their site visits, we find that 186 of these reports prominently use the term "site visit" in the report titles, in various forms such as "site visit briefing," "site visit report," or "site visit bulletin." For the remaining reports, 8 reports mention "site visit" as one of the information sources in the textual body of the reports. In total, 77.6% (= (186+8)/250) of the randomly selected analyst reports explicitly disclose analysts' recent site visits.

credibility of the earnings forecasts issued by visiting analysts after site visits. This is consistent with the insights obtained from our interviews, as noted by one interviewed analyst: "The credibility of such a report is greatly enhanced if my interpretation of the past and my predictions of the future are echoed by company managers. This not only boosts my confidence in my reports, but also makes them more convincing for the readers."

Following prior studies (e.g., Abarbanell, Lanen, and Verrecchia 1995; Clement and Tse 2003; Keung 2010), we measure the perceived credibility of earnings forecasts using the forecast response coefficient for forecast revisions. We then investigate whether the market reaction to the same unit of forecast revision is larger when such forecast revisions are issued by visiting analysts after site visits. For this purpose, we estimate the following regression model:

$$CAR_{i,j,t} = \alpha + \beta_1 EF\_Rev_{i,j,t} + \beta_2 Visit\_prev\_month_{i,j,t} + \beta_3 EF\_Rev_{i,j,t} \times Visit\_prev\_month_{i,j,t} + \boldsymbol{\Theta}\ \boldsymbol{Controls} + \varepsilon_{k,j,t}\ , \quad (5)$$

CAR is measured as the three-day cumulative size-adjusted return surrounding the earnings forecast revision. Earnings forecast revision (*EF_Rev*) is measured as the difference between an analyst's annual earnings forecast for the current year and his/her own prior earnings forecast, scaled by the stock price at the end of the month before the revision. To capture analysts' site visit activities, we use the indicator variable $Visit\_prev\_month_{i,j,t}$, which equals 1 if analyst *i* visited firm *j* in the month before the current forecast revision, and 0 otherwise. We require the sample firms to have at least one forecast revision observation with *Visit_ prev_month* = 1 and at least one forecast revision observation with *Visit_ prev_month* = 0 over the sample period. Of the sample of 17,317 forecast revisions, 11.97% are issued by visiting analysts in the month after their site visits (i.e., *Visit_ prev_month* = 1). The variable of interest is the interaction term *EF_Rev*× *Visit_ prev_month*. The estimated coefficient on this variable captures the incremental effect of analysts' site visits on the forecast response coefficient.

Table 9 reports the regression results. Consistent with prior literature, the market reaction is positively associated with forecast revisions (t = 6.26). More importantly, investors' market reactions appear to be more responsive to the forecast revisions issued by visiting analysts than those issued by non-visiting analysts, as evidenced by the positive coefficient on the interaction term (t = 2.35). These findings triangulate the main finding by showing that site visits increase the credibility of visiting analysts' forecast revisions.

5.5 Site visit and local advantage

Prior studies find that local analysts' earnings forecasts are more accurate than those issued by non-local analysts, likely due to local analysts' information advantage (Malloy 2005; Bae et al. 2008). Given our finding that analysts' forecast accuracy improves after site visits, two questions arise. First, does conducting site visits contribute to the local analysts' advantage? Second, can non-local analysts overcome their disadvantage by conducting site visits?

Prior research suggests that site visits can be an information channel behind the local analysts' advantage. For example, Coval and Moskowitz (2001) suggest that "investors located near a firm can visit the firm's operations, talk to suppliers and employees, as well as assess the local market conditions in which the firm operates." Bae et al. (2008) propose that local analysts have an advantage because they are able to gain access to a firm's soft information, make on-site observations of the firm's operation activities, and interact directly with the firm's executives. To examine whether conducting site visits at least partially explains local analysts' information advantage, we construct an indicator variable for non-local analysts (*Non-local*). We then estimate the following regression to investigate whether the effect of geographic proximity on forecast accuracy continues to hold after controlling for the effect of site visits:

$$Rel\_Accuracy_{i,j,t} = \alpha + \beta_1 Non\_local_{i,j,t} + \beta_2 Visit\_Freq_{i,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{i,j,t} \quad (6)$$

The dependent variable, *Rel_Accuracy,* and *Visit_freq* are as defined in Section 5.3. The indicator variable, *Non_local,* equals 1 for the analysts whose brokerage firms are more than 400 kilometers (or 250 miles) away from the visited firm's headquarters, and 0 otherwise.

Table 10 presents the regression results.[21] Column (1) confirms that non-local analysts' forecasts are less accurate than those issued by local analysts. The coefficient on *Non-local* is significantly negative (t = -2.86). Column (2) shows that consistent with the results reported in previous sections, forecasts issued by analysts with more site visits are more accurate, as shown by the positive coefficient on *Visit_freq* (t = 8.15). Column (3) includes both the local analyst indicator and site visit frequency. The coefficient on *Non_local* remains significantly negative (t = -2.39). The coefficient on *Visit_freq* also remains statistically significant (t = 7.99). The similar magnitude of the coefficients on *Non_local* in columns (1) and (3) (-0.0190 versus -0.0168) indicates that site visits are not the primary driver of local analysts' advantage.

We then investigate whether non-local analysts can overcome their disadvantage by conducting site visits. As non-local analysts benefit more from site visits than local analysts, we add an interaction term of *Non-local* and *Visit_freq* to Equation (6) and report the regression results in Column (4) of Table 10. The coefficient on *Non_local* continues to be significantly negative and the coefficient on *Visit_freq* continues to be significantly positive, although with a smaller magnitude. The coefficient on the interaction term is also significantly positive (t = 5.24), suggesting that the positive effect of site visits on forecast accuracy is more pronounced for non-local analysts than for local analysts. The net effect for non-local analysts who conduct site visit once is the sum of the three coefficients: -0.0300 + 0.0108 + 0.0364 = 0.0172, with a two-

[21] Following Bae et al. (2008), we require that at least one local analyst and one non-local analyst follow the sample firm-years. Such a requirement helps alleviate the concern that local and non-local analysts choose to follow firms with different fundamentals. In addition, we exclude the stale earnings forecasts, i.e., those issued more than 300 days before earnings announcements. The final sample for this test consists of 17,714 earnings forecasts from July 2009 to 2012.

sided p-value of 0.094 (untabulated). This suggests that the forecasts issued by non-local analysts who conduct one site visit are as accurate as those issued by local analysts who do not conduct site visits. If non-local analysts conduct two or more site visits to a firm (i.e., *Visit_freq* = 2), their forecasts are more accurate than those issued by local analysts who do not conduct site visits ($-0.0300 + 2 \times 0.0108 + 2 \times 0.0364 = 0.0644$, with a p-value of 0.01, untabulated).

In summary, these analyses suggest that site visits are not the primary drivers of the local analysts' advantage, as suggested in prior studies. The local advantage probably arises from other information channels, such as social networking with executives and employees and a better understanding of the local market and economic situation. However, our analyses indicate that conducting site visits can help non-local analysts to overcome their information disadvantage.

5.6 Why do not all analysts conduct site visits?

Our results so far suggest that analysts obtain useful information from their site visits (e.g., more accurate forecasts). One natural question that arises is why not all analysts conduct site visits to the firms they follow. In this section, we investigate the factors that affect analysts' site visit decisions. We argue that analysts' site visit decisions are affected by the tradeoff between the costs and benefits of conducting site visits. On the cost side, we expect that analysts are less likely to conduct site visits to firms located farther away from them or if they have more limited financial sources (i.e., working for a smaller broker). On the benefit side, as discussed above, we find that analysts' visits to manufacturing firms, firms with more tangible assets, and firms with more concentrated business are more useful than other visits. Thus, we expect that financial analysts are more likely to visit these firms. We use the indicators for manufacturing firms (*Manufacture*), firms with high asset tangibility (*Tangibility*), and firms with high business concentration (*Concentration*) as the proxies for the benefits.[22]

To examine individual analysts' decision to conduct site visits to a specific firm in a specific year, we generate a sample of analyst-firm-year observations where the analyst has issued at least one earnings forecast or stock recommendation for this firm in the previous or the current year. After imposing other data requirements, the final sample consists of 49,553 analyst-firm-year observations for 1,395 unique firms over the sample period of 2009-2012.

To capture the site visit decision, we use an indicator variable, *Visit_firm*, which equals one when an analyst conducts a site visit to the firm in the current year and zero otherwise. *Visit_firm* is coded as one for 25.1% of the sample. Table 11 reports the logistic regression results. First, consistent with our expectation on the costs of conducting site visits, we find that the coefficient on the geographical distance (*Distance*) is significantly negative (z-value = -7.84) and that on brokerage size is significantly positive (z-value= 5.38). These findings indicate that analysts are less likely to visit firms farther away from them or when they have more limited financial resources. On the benefit side, we find that analysts are more likely to conduct site visits to firms with higher level of asset tangibility and firms with higher level of business concentration; the coefficients on *Tangibility* and *Concentration* are significantly positive (z-value=2.77 and 2.84, respectively). We also find that the coefficient on *Manufacture* is positive, but not statistically significant (z-value =1.64).

We include a series of control variables in the regression. We find that analysts are more likely to visit a firm if they have a favorable opinion towards it (*StrongBuy*), if the firm has a higher disclose rating (*Disclosure_rating*) and more analysts following (*ANA*), or if the firm is

[22] We acknowledge that some of the factors affect both the costs and benefits. For example, while the cost of conducting site visits increases with geographical distance, the benefit also increases with it as analysts generally know less about geographically remote firms and thus the information obtained from the site visits is more important. As such, the results reflect the net effect. Also, this is by no means a comprehensive list of proxies for the costs and benefits of conducting site visits.

older (*Age*), but are less likely to visit state-owned enterprises (*SOE*).

Overall, these findings are consistent with the notion that the likelihood of analysts' site visits increases with the expected benefits and decreases with the costs adherent to conducting site visits.

6 Conclusion

This study examines how a particular information acquisition activity, i.e., corporate site visits, affects analysts' forecast performance. Unlike prior studies that use indirect proxies for analysts' efforts to acquire information, we exploit the mandatory disclosure of analysts' corporate site visits in China and directly capture analysts' information acquisition activities. Using a difference-in-differences approach, we find that visiting analysts experience an improvement in forecast accuracy after site visits compared to analysts who do not conduct site visits. In addition, the improvement is more pronounced for manufacturing firms, firms with more tangible assets, and firms with more concentrated business lines. Moreover, the improvement is larger when the visits are conducted by analysts only, when the visiting analysts are located at a greater geographical distance from the visited firms, and when the analysts' site visits are preceded by fewer site visits.

We conduct several additional analyses and find that our results are not driven by the potentially different attributes of visiting and non-visiting analysts or firms' selective disclosure during site visits. Consistent with the notion that analysts obtain an information advantage through site visits, we document a stronger market response to the forecast revisions issued by visiting analysts than those by non-visiting analysts. Furthermore, we present evidence that site visits help non-local analysts to overcome their information disadvantage. Lastly, we conduct a determinant analysis and find that the likelihood of analysts' site visits increases with the expected benefits and decreases with the costs adherent to conducting site visits.

This study contributes to the financial analyst literature by presenting evidence that the corporate site visit, a form of active information acquisition, has a positive effect on analysts' forecast performance. Our empirical results on forecast accuracy are largely consistent with the insights obtained from our interviews with sell-side analysts, firm IR managers, and fund managers. The richness of the data provides many future research opportunities. For example, some analysts conduct site visits to firms that they do not cover. It will be interesting to examine the benefit of site visits to these analysts. Are they obtaining information on the peers, customers, suppliers of the firms they cover? Many analysts offer site visit services to their buy-side clients. It will be interesting to examine how exactly analysts benefit from offering such services. Do they obtain more commissions for their brokers? Do they obtain more votes as the top analysts of the industry? Starting from 2013, the detailed meeting minutes of site visits are available on the SZSE website. A textual analysis of these meeting transcripts can potentially enrich our understanding of the information acquisition process during the site visits. We leave these interesting questions to future research.

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APPENDIX A
A site visit example: Extract of the 2011 annual report of Shenzhen Airport Co. Ltd.

During the reporting period, the company follows the information disclosure guidelines and investor relationship management bylaws issued by the SZSE. The company communicates with investors by hosting site visits and holding one-on-one meetings with institutional investors and by taking phone calls from individual investors.[23] During the reporting period, the company meets with 54 individuals from various institutions. During these visits, the company discusses its general operations and future strategy with investors based on public information. The company does not selectively disclose information to investors. The site visits are detailed as follows.

Time	Visitor	Topics of discussion and materials provided
Jan. 5, 2011	Everbright Securities	Recent company updates
Jan. 11, 2011	China International Capital Co. Ltd.	Recent company updates
Jan. 21, 2011	Changjiang Securities, China Investment Securities	Progress of construction and recent operations
Mar. 23, 2011	CITIC Securities	Recent company updates
Mar. 24, 2011	Changjiang Securities, Baoying Fund Management, Huatai-PineBridge Investments	Company operation and construction expansion
Apr. 12, 2011	GF Securities, China Merchants Fund	Construction of T3, and the business circumstances of main operations and non-flight-related operations
Apr. 20, 2011	Guosen Securities, Harvest Fund, Guotai AMC, Sino Life Insurance, Dacheng Fund	Company fundamentals
May 12, 2011	Taikang AMC	Company fundamentals
May 19, 2011	Changjiang Securities, Chengrui Investment	Construction of T3 and recent company updates
June 10, 2011	Ping An Securities	Recent company updates
June 13, 2011	Hongyuan Securities	Convertible bond and business circumstances
June 23, 2011	Investor Conference hosted by Changjiang Securities	Introduction of current business picture and topical issues
Aug. 16, 2011	Bosera Securities, Dacheng Securities	Fundamentals and convertible bond
Aug. 19, 2011	Ping An Annuity Insurance	Company fundamentals
Sep. 29, 2011	JS Cresvale Securities	Company fundamentals
Nov. 7, 2011	UBS	Company fundamentals
Nov. 17, 2011	China Merchants Fund	Company fundamentals
Dec. 8, 2011	Upstone Capital, Kangqiao Asset, Houde Investment	Company fundamentals
Dec. 14, 2011	Guotai Junan	Company fundamentals
Dec. 15, 2011	GF Securities	Company fundamentals
Dec. 19, 2011	Everbright Securities	Company fundamentals

[23] Companies occasionally include telephone interviews, performance illustration webinars, email exchanges, non-deal road shows, investor conferences, industry summits, industry forums, annual broker conferences, non-deal road shows, and one-on-one meetings with managers in this section. We include only the site visit events (held at company headquarters or subsidiaries) in the current study.

APPENDIX B
Variable definitions

Dependent variable (site visit event-analyst group level variables)		
$\Delta Accuracy_{k,j,t} = -(Post\_Visit\_AFE_{k,j,t} - Pre\_Visit\_AFE_{k,j,t})$		
	=	-1 times the change in the absolute forecast error of analyst group k (visiting or non-visiting analysts) for firm j from the six months before the site visit conducted on day t to one month after. A positive value implies an improvement in forecast accuracy from the pre- to post-visit periods. For each analyst group, we identify the most recent annual EPS forecast issued by each analyst within the group in the six months prior to the site visit event, calculate the group mean as the group consensus forecast, and calculate *Pre_Visit_AFE* as the absolute difference between the group consensus EPS forecast and actual EPS, scaled by the stock price at the beginning of the year, expressed in percentage. To calculate *Post_Visit_AFE*, we identify the first forecast made by the analysts in the same group in the month after the site visit and calculate their forecast consensus and the absolute forecast error for the same group in the period after the site visit. For the analysts who do not update their forecasts in the post-visit period, we assume their post-visit forecasts to be the same as their pre-visit forecasts. If an analyst does not issue a pre-visit earnings forecast (but does issue a post-visit earnings forecast), then we use the mean forecast of all of the other analysts' forecasts in the pre-visit period as the pre-visit forecast for such an analyst when calculating the forecast accuracy change.

Key independent variable (site visit event-analyst group level variables)		
$Visit_{k,j,t}$	=	An indicator variable that equals 1 for the visiting analyst group and 0 for the non-visiting analyst group. An analyst is a visiting analyst if he/she visits firm j on a site visit event day t. The analysts who follow the same firm but do not visit it in the six months before or one month after the site visit of interest are referred to as non-visiting analysts.

Variables for cross-sectional analyses (firm-year level and visiting group level variables)		
$Manufacture_{j,t}$	=	An indicator variable that equals 1 when the firm is a manufacturing firm, and 0 otherwise.
$Tangibility_{j,t}$	=	An indicator variable that equals 1 when the ratio of PP&E over total assets is greater than or equal to the sample median, and 0 otherwise.
$Concentration_{j,t}$	=	An indicator variable that equals 1 when the firm's Herfindahl-Hirschman index (HHI) based on segment revenue is greater than or equal to the sample median, and 0 otherwise. Segment revenue HHI equals the sum of squares of the ratio of segment revenue to the total revenue for firm j in the current year.
$AnalystOnly_{k,j,t}$	=	An indicator variable for analyst-only visits. It equals 1 if all of the visitors are sell-side analysts, and 0 otherwise.
$Remote_{k,j,t}$	=	An indicator variable for non-local analysts. It equals 1 if non-local analysts outnumber the local analysts in the visiting groups, and 0 otherwise. Non-local analysts are those whose brokerage firms are located more than 400 kilometers (250 miles) away from the visited

		firm's headquarters.
$Unpreceded_{k,j,t}$	=	An indicator variable for firms with fewer preceding visits within the month before the site visit of interest. It equals 1 if the number of preceding site visits that occurs within the one-month window before the current site visit *t* is below the sample median for the visiting group, and 0 otherwise. This variable is coded as 0 for non-visiting groups.
Control variables		
$\Delta Horizon_{k,j,t}$	=	Change in forecast horizon, calculated as the log transformation of the decrease in the average forecast horizon of analyst group *k* (visiting or non-visiting group) from the pre- to post-visit periods. The forecast horizon is defined as the number of days between the forecast issue date and corresponding earnings announcement date.
$Firmexp_{k,j,t}$	=	Analyst-firm-specific experience, calculated as the log transformation of the average firm-specific experience of all of the analysts in analyst group *k* for firm *j*. Firm-specific experience is calculated as the number of years between an analyst's first forecast for firm *j* and his/her current forecast for firm *j*.
$Brokersize_{k,j,t}$	=	Broker size, defined as the average number of analysts working for the brokers in group *k*.
$ANA\_group_{k,j,t}$	=	Group size, calculated as the log transformation of the number of analysts in group *k*.
$MV_{j,t}$	=	Firm size, calculated as the log transformation of the market value of equity of firm *j* at the end of the last fiscal year.
$Inst\_holding_{j,t}$	=	Institutional ownership, calculated as the ownership percentage of institutional investors.
$Indep_{j,t}$	=	Board independence, calculated as the ratio of the number of independent directors to the total number of directors for firm *j* in the current year.
$BM_{j,t}$	=	Book-to-market ratio, calculated as the book value of equity divided by the market value of equity.
$Growth_{j,t}$	=	Revenue growth, defined as the revenue in year *t* divided by the revenue in year *t-1*.
$Loss_{j,t}$	=	Loss indicator that equals 1 if the net income is negative in year *t*, and 0 otherwise.
$BHAR_{j,t}$	=	The buy and hold market-adjusted returns in year t.

TABLE 1
Sample selection

This table reports the sample selection procedure for our sample of analysts' site visits during 2009-2012.

		No. of total site visits	No. of total firms
1.	Site visits involving sell-side analysts	18,259	1,298
2.	Combining site visits with adjacent event dates as one event and using the first day as the event day	16,913	1,269
3.	Requiring visiting analysts as a group to issue at least one earnings forecast during the 18 months before the forthcoming earnings announcement date	9,730	1,105
4.	Requiring visiting and non-visiting analysts to issue at least one earnings forecast during the six months before and one month after the site visit	7,154	965
5.	Dropping financial firms and events with missing values for control variables	6,651	931

TABLE 2
Descriptive statistics

This table presents the summary statistics of the variables used in the main analyses. The sample includes 6,651 site visit events and 13,302 observations with required data, including 6,651 observations from the visiting groups and 6,651 observations from the non-visiting groups. Please see Appendix B for the variable definitions. ***, **, and * indicate that the difference between visiting and non-visiting groups in the corresponding variable is statistically significant at the 0.01, 0.05, and 0.10 levels, respectively.

Variables	Obs.	Mean	STD	Q1	Median	Q3
For visiting analyst group						
Pre-visit forecast errors	6,651	1.241	1.955	1.609	0.659*	0.231
Post-visit forecast errors	6,651	1.077***	1.771	1.359	0.533***	0.183
ΔAccuracy	6,651	0.164***	0.869	0.000	0.000***	0.090
Pre-visit horizon	6,651	183.765***	67.532	126.400	186.000***	241.000
Post-visit horizon	6,651	126.125***	66.916	71.000	125.000***	185.000
ΔHorizon (raw)	6,651	57.641***	30.182	33.000	53.000***	77.000
Firmexp	6,651	2.435***	1.865	1.000	2.000***	3.000
Brokersize	6,651	33.691***	12.559	26.000	33.333***	42.000
ANA_group	6,651	1.385***	0.934	1.000	1.000***	1.000
For non-visiting analyst group						
Pre-visit forecast errors	6,651	1.242	2.038	1.588	0.699	0.248
Post-visit forecast errors	6,651	1.201	2.103	1.524	0.671	0.237
ΔAccuracy	6,651	0.041	0.557	0.000	0.000	0.003
Pre-visit horizon	6,651	190.310	64.901	129.537	195.800	244.333
Post-visit horizon	6,651	121.053	66.322	66.200	121.000	180.000
ΔHorizon (raw)	6,651	69.256	23.491	52.889	67.612	84.316
Firmexp	6,651	2.243	1.236	1.250	2.000	3.000
Brokersize	6,651	28.774	7.424	24.500	28.571	32.750
ANA_group	6,651	7.234	5.120	3.000	6.000	10.000
Control variables						
MV (raw, in millions RMB)	6,651	10,317	15,002	3,113	5,464	10,527
NI_std	6,651	0.050	0.050	0.020	0.040	0.070
Inst_holding	6,651	0.440	0.240	0.250	0.440	0.630
Indep	6,651	0.370	0.060	0.330	0.330	0.400
BM	6,651	0.360	0.200	0.210	0.320	0.460
Growth	6,651	0.280	0.340	0.080	0.230	0.390
Loss	6,651	0.010	0.100	0.000	0.000	0.000
BHAR	6,651	0.150	0.470	-0.100	0.010	0.290
Variables for the cross-sectional analyses						
Manufacture	6,651	0.661	0.473	0.000	1.000	1.000
PP&E/Assets	6,651	0.232	0.165	0.105	0.200	0.317
SegHHI	6,567	0.604	0.250	0.411	0.633	0.796
AnalystOnly (visiting group)	6,651	0.370	0.483	0.000	0.000	1.000
Remote (visiting group)	6,648	0.727	0.446	0.000	1.000	1.000
Unpreceded (visiting group) *(raw number of preceding visits)*	6,651	1.690	1.800	0.000	1.000	3.000

TABLE 3

The change in forecast accuracy for visiting and non-visiting analyst groups around site visits

This table presents the OLS regression results of the forecast accuracy change on the site visit indicator and control variables:

$$\begin{aligned} \Delta Accuracy_{k,j,t} &= \alpha + \beta Visit_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} \\ &+ \gamma_4 ANA\_group_{k,j,t} + \gamma_5 MV_{j,t} + \gamma_6 NI\_std_{j,t} + \gamma_7 Inst\_holding_{j,t} + \gamma_8 Indep_{j,t} \\ &+ \gamma_9 BM_{j,t} + \gamma_{10} Growth_{j,t} + \gamma_{11} Loss_{j,t} + \gamma_{12} BHAR_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}. \end{aligned}$$

The dependent variable is the forecast accuracy change for an analyst group from the pre- to post-visit periods (*ΔAccuracy*). The full sample consists of 13,302 observations from 2009 to 2012. For each site visit, there is one observation for the visiting analyst group and one observation for the non-visiting analyst group. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate that the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. Please see Appendix B for variable definitions.

	Coeff. *(t-value)*
Visit (H1: +)	0.1292***
	(5.13)
ΔHorizon	0.0582***
	(8.23)
Firmexp	-0.0014
	(-0.20)
Brokersize	-0.0384*
	(-1.92)
ANA_group	0.0073
	(0.75)
MV	-0.0265**
	(-2.53)
NI_std	0.2977***
	(4.74)
Inst_holding	0.0444
	(0.97)
Indep	-0.0176
	(-0.26)
BM	0.1235***
	(2.58)
Growth	-0.0380
	(-1.12)
Loss	0.2506**
	(2.36)
BHAR	0.0107
	(0.80)
Industry Fixed Effects	Yes
Observations	13,302
Adj. R^2	0.039

TABLE 4
The effect of firm characteristics on the usefulness of analysts' site visits

This table presents the results from the following regression:

$$\Delta Accuracy_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Firm\_char_{j,t} + \beta_3 Visit_{k,j,t} \times Firm\_char_{j,t} + \boldsymbol{\gamma\ Controls} + \varepsilon_{k,j,t}\ .$$

The dependent variable is the forecast accuracy change for an analyst group from the pre- to post-visit periods (*ΔAccuracy*). *Firm_char* is the indicator for manufacturing firms (*Manufacture*) in Column (1), the asset tangibility level (*Tangibility*) in Column (2) and the business concentration level (*Concentration*) in Column (3).

The full sample consists of 13,302 observations from 2009 to 2012. For each site visit, there is one observation for the visiting analyst group and one observation for the non-visiting analyst group. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate that the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. Please see Appendix B for variable definitions.

TABLE 4 (Cont'd)

	Column (1) *Firm_char* = *Manufacture*	Column (2) *Firm_ char* = *Tangibility*	Column (3) *Firm_ char* = *Concentration*
Visit	0.1096***	0.1121***	0.1005***
	(4.28)	(6.25)	(3.00)
Firm_char	-0.0116	0.0027	0.0127
	(-0.31)	(0.49)	(1.13)
Visit×Firm_char (*H2:*+)	0.0294**	0.0354**	0.0524***
	(2.08)	(2.30)	(2.81)
ΔHorizon	0.0581***	0.0584***	0.0591***
	(8.21)	(8.12)	(7.61)
Firmexp	-0.0017	-0.0031	-0.0038
	(-0.24)	(-0.40)	(-0.60)
Brokersize	-0.0377*	-0.0365*	-0.0386*
	(-1.87)	(-1.82)	(-1.87)
ANA_group	0.0072	0.0078	0.0091
	(0.73)	(0.80)	(0.93)
MV	-0.0265**	-0.0262**	-0.0280***
	(-2.52)	(-2.48)	(-2.74)
NI_std	0.2974***	0.3215***	0.2969***
	(4.73)	(5.60)	(4.18)
Inst_holding	0.0445	0.0416	0.0370
	(0.97)	(0.92)	(0.78)
Indep	-0.0177	-0.0081	-0.0204
	(-0.26)	(-0.12)	(-0.31)
BM	0.1236**	0.1165**	0.1229**
	(2.58)	(2.36)	(2.57)
Growth	-0.0380	-0.0380	-0.0379
	(-1.12)	(-1.14)	(-1.10)
Loss	0.2506**	0.2453**	0.2481**
	(2.36)	(2.32)	(2.33)
BHAR	0.0107	0.0098	0.0092
	(0.80)	(0.70)	(0.71)
Industry Fixed Effects	Yes	Yes	Yes
Observations	13,302	13,302	13,134
Adj. R^2	0.039	0.039	0.040

TABLE 5
The effect of visitors' characteristics on the usefulness of analysts' site visits

This table presents the results of the following regression:

$$\Delta Accuracy_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Visit_{k,j,t} \times Visit\_char_{k,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{k,j,t}$$

The dependent variable is the forecast accuracy change for an analyst group from the pre- to the post-visit periods (*ΔAccuracy*). *Visit_char* is the analyst-only visit indicator (*AnalystOnly*) in Column (1), the remote visit indicator (*Remote*) in Column (2), the indicator for fewer proceeding site visits (*Unpreceded*) in Column (3). These variables are coded as 0 for non-visiting groups. The full sample consists of 13,302 observations from 2009 to 2012, with one for visiting and one for non-visiting analyst group for each site visit. The t-values are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate the 0.01, 0.05, and 0.10 significance levels. Please see Appendix B for variable definitions.

	Column (1) *Visit_char = AnalystOnly*	Column (2) *Visit_char = Remote*	Column (3) *Visit_char = Unpreceded*
Visit	0.1034***	0.0933***	0.1093***
	(4.23)	(4.01)	(5.58)
Visit×Visit_char (H3: +)	0.0787***	0.0509***	0.0318***
	(7.07)	(9.90)	(2.84)
ΔHorizon	0.0561***	0.0580***	0.0591***
	(8.01)	(8.20)	(8.19)
Firmexp	-0.0013	-0.0005	-0.0017
	(-0.20)	(-0.07)	(-0.25)
Brokersize	-0.0308	-0.0385*	-0.0378*
	(-1.63)	(-1.95)	(-1.90)
ANA_group	0.0115	0.0083	0.0053
	(1.22)	(0.84)	(0.58)
MV	-0.0277***	-0.0276***	-0.0249**
	(-2.80)	(-2.64)	(-2.44)
NI_std	0.3159***	0.3024***	0.2877***
	(5.52)	(4.86)	(4.82)
Inst_holding	0.0456	0.0429	0.0464
	(1.02)	(0.95)	(1.02)
Indep	-0.0179	-0.0134	-0.0176
	(-0.29)	(-0.21)	(-0.27)
BM	0.1176**	0.1231**	0.1211**
	(2.50)	(2.55)	(2.56)
Growth	-0.0388	-0.0377	-0.0377
	(-1.20)	(-1.11)	(-1.11)
Loss	0.2491**	0.2474**	0.2485**
	(2.33)	(2.33)	(2.35)
BHAR	0.0113	0.0108	0.0104
	(0.86)	(0.79)	(0.80)
Industry Fixed Effects	Yes	Yes	Yes
Observations	13,302	13,296	13,302
Adj. R^2	0.043	0.040	0.039

TABLE 6
Analysts' site visits and the level of forecast accuracy

This table presents the results from the following regression:

$$Accuracy_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Post_{k,j,t} + \beta_3 Visit_{k,j,t} \times Post_{k,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{k,j,t}$$

Columns (1) and (2) report the regression results of the forecast accuracy level on the visit indicator and control variables before and after the site visit date, respectively. Column (3) reports the regression results of the forecast accuracy level on the visit indicator, the post-visit indicator, their interaction term, and the control variables.

Accuracy is calculated as -1 times the forecast errors in the pre- (*Pre_visit_AFE*) or post-visit (*Post_visit_AFE*) periods. A higher value implies a higher level of forecast accuracy. The post-visit indicator (*Post*) equals 1 for post-site-visit observations, and 0 otherwise. *Horizon* is the forecast horizon, calculated as the number of calendar days between the forecast issue date and corresponding earnings announcement date. Please see Appendix B for definitions of other variables. The full sample consists of 26,604 observations from 2009 to 2012. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate that the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

TABLE 6 (Cont'd)

	Column (1) *Accuracy* before site visit	Column (2) *Accuracy* after site visit	Column (3) *Accuracy* Full sample
Visit	-0.0068	0.1056***	-0.0049
	(-0.35)	(3.07)	(-0.24)
Post			0.0451***
			(6.24)
Visit×Post (H1: +)			0.1084***
			(5.67)
Horizon	-0.6069***	-0.5879***	-0.5974***
	(-3.04)	(-3.28)	(-3.15)
Firmexp	-0.2380***	-0.2483***	-0.2433***
	(-4.29)	(-4.97)	(-4.63)
Brokersize	0.0212	-0.0187	0.0013
	(0.42)	(-0.27)	(0.02)
ANA_group	0.1263***	0.1144***	0.1204***
	(6.63)	(6.08)	(6.63)
MV	0.1505	0.1364	0.1435
	(1.47)	(1.47)	(1.47)
NI_std	-0.0016	-0.0019	-0.0018
	(-0.94)	(-1.21)	(-1.07)
Inst_holding	-0.0536	-0.0462	-0.0498
	(-0.20)	(-0.21)	(-0.21)
Indep	-0.9623*	-1.0193**	-0.9907**
	(-1.91)	(-2.21)	(-2.06)
BM	-1.3967***	-1.2814***	-1.3390***
	(-4.13)	(-3.87)	(-4.01)
Growth	-0.0001***	-0.0001***	-0.0001***
	(-3.03)	(-3.33)	(-3.17)
Loss	-3.6138***	-3.2916***	-3.4527***
	(-19.21)	(-28.35)	(-23.87)
BHAR	-0.0035	0.0069	0.0017
	(-0.03)	(0.07)	(0.01)
Industry Fixed Effects	Yes	Yes	Yes
Observations	13,302	13,302	26,604
Adj. R^2	0.273	0.263	0.269

TABLE 7

The change in forecast accuracy for visiting and non-visiting analyst groups around site visits: (1) excluding non-visiting analysts that do not conduct site visits (2) excluding analysts who issued strong-buy recommendations or had investment banking relationship

This table replicates Table 3 after imposing additional data requirement. Column (1) reports the results after excluding non-visiting analysts that do not conduct site visits to the firm over the sample period. This additional data requirement results in a sample of 10,788 observations. Column (2) reports the results after excluding analysts who issued strong-buy recommendations in the year prior to site visits or those who had investment banking relationship with the firm in the past. This additional data requirement results in a sample of 9,798 observations. The regression model is:

$$\begin{aligned} \Delta Accuracy_{k,j,t} = {} & \alpha + \beta Visit_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} \\ & + \gamma_4 ANA\_group_{k,j,t} + \gamma_5 MV_{j,t} + \gamma_6 NI\_std_{j,t} + \gamma_7 Inst\_holding_{j,t} + \gamma_8 Indep_{j,t} \\ & + \gamma_9 BM_{j,t} + \gamma_{10} Growth_{j,t} + \gamma_{11} Loss_{j,t} + \gamma_{12} BHAR_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}. \end{aligned}$$

The dependent variable is the forecast accuracy change for an analyst group from the pre- to post-visit periods (*ΔAccuracy*). For each site visit, there is one observation for the visiting analyst group and one observation for the non-visiting analyst group. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate that the coefficients are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests. Please see Appendix B for variable definitions.

Table 7 (Cont'd)

	Column (1) *Coeff.* *(t-value)*	Column (2) *Coeff.* *(t-value)*
Visit (H1: +)	0.1184***	0.1446***
	(6.94)	(5.67)
ΔHorizon	0.0469***	0.0577***
	(5.44)	(5.81)
Firmexp	-0.0011	0.0013
	(-0.13)	(0.32)
Brokersize	-0.0321*	-0.0378*
	(-1.85)	(-1.89)
ANA_group	0.0175***	0.0131
	(3.93)	(0.91)
MV	-0.0296***	-0.0311**
	(-3.46)	(-2.28)
NI_std	0.3579***	0.2272***
	(4.53)	(3.20)
Inst_holding	0.0492	0.0530
	(1.18)	(1.00)
Indep	0.0054	-0.0665
	(0.05)	(-0.74)
BM	0.1234**	0.1401**
	(2.00)	(2.43)
Growth	-0.0222	-0.0545
	(-0.59)	(-1.27)
Loss	0.1917***	0.2696**
	(12.24)	(2.47)
BHAR	0.0002	0.0140
	(0.01)	(0.71)
Industry Fixed Effects	Yes	Yes
Observations	10,788	9,798
Adj. R^2	0.034	0.041

TABLE 8
Comparisons based on the same-analyst observations

This table presents the results from the following regression:

$$Rel\_Accuracy_{i,j,t} = \alpha + \beta Visit\_Freq_{i,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{i,j,t}$$

In Columns (1), we focus on analyst-year pairs where the analyst visits some firms but not other firms in the same year. We require that the analyst issues forecasts for both types of firms. The sample consists of 26,103 analyst-firm-year observations from 2009 to 2012.

In Column (2), we focus on analyst-firm pairs, where the analyst visits the firm in some years, but not in other years. We further require that the analyst issues forecasts for the firm in both periods. The sample consists of 5,469 analyst-firm-year observations from 2009 to 2012.

The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Variable definition:

$Rel\_Accuracy_{i,j,t}$	= analyst *i*'s relative forecast accuracy, measured as the difference between the forecast error of analyst *i* for firm *j*'s year *t* earnings and the average forecast error across all analyst forecasts of firm *j*'s year *t* earnings, divided by the average absolute forecast error across all analyst forecasts of firm *j*'s year *t* earnings, then multiplied by -1. A higher value implies a higher level of forecast accuracy. For each analyst, we calculate the forecast error using the analyst's most recent annual earnings forecast issued in the year before the firm's earnings announcement.
$Visit\_freq_{i,j,t}$	= site visit frequency, measured as the number of site visits conducted by analyst *i* in the six-month period before the issuance date of the most recent earnings forecast used to calculate the analyst's forecast accuracy; or the period between the last year's earnings announcement date and the issuance date of the most recent earnings forecast, whichever period is longer. *Visit_freq* equals 2 (1, 0) if analyst *i* visited firm *j* two or more (once, zero) times during this period.
$Horizon_{i,j,t}$	= forecast horizon, calculated as the number of calendar days between the forecast issue date and corresponding earnings announcement dates.
$Firmexp_{i,j,t}$	= analyst's firm-specific experience, calculated as the log transformation of the time interval in years between analyst *i*'s first forecast for firm *j* and his/her forecast at time *t* for firm *j*.
$Genexp_{i,t}$	= analyst's general experience, calculated as the log transformation of the time interval in years between analyst *i*'s first forecast in the CSMAR database and his/her current forecast at time *t*.
$Brokersize_{i,t}$	= broker size, calculated as the number of analysts working for the brokerage firm with which analyst *i* is associated.
$Numind_{i,t}$	= industry coverage, calculated as the log transformation of the number of CSRC Level-2 industries analyst *i* covers.
$MV_{j,t}$	= firm size, calculated as the log transformation of the market value of equity of firm *j* at the end of last fiscal year.

TABLE 8 (Cont'd)

	Column (1) *Coeff.* *(t-value)*	Column (2) *Coeff.* *(t-value)*
*Visit_freq_*	0.0462***	0.0413***
	(10.63)	(4.36)
Horizon	-0.2819***	-0.2608***
	(-5.74)	(-4.31)
Firmexp	0.1152***	0.0642
	(6.30)	(1.55)
Genexp	0.0138	-0.0109
	(1.06)	(-0.75)
Brokersize	0.0158	0.0065
	(0.93)	(0.21)
Numind	-0.0282	-0.0077
	(-0.71)	(-0.22)
MV	0.0102*	0.0010
	(1.74)	(0.07)
Industry Fixed Effects	Yes	Yes
Observations	26,103	5,469
Adj. R^2	0.090	0.083

TABLE 9
Site visits and market reaction

This table presents the results from the following regression:

$$CAR_{i,j,t} = \alpha + \beta_1 EF\_Rev_{i,j,t} + \beta_2 Visit\_prev\_month_{i,j,t} + \beta_3 EF\_Rev_{i,j,t} \times Visit\_prev\_month_{i,j,t} + \boldsymbol{\Theta} Controls + \varepsilon_{k,j,t}$$

The full sample consists of 17,317 earnings forecast revisions issued between 2009 and 2012. We require the sample firms to have at least one earnings forecast revision with $Visit\_prev\_month$ = 1 and at least one earnings forecast revision with $Visit\_prev\_month$ = 0. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Variable definition:

$CAR_{i,j,t}$	= cumulative abnormal returns in the (-1, +1) window around the earnings forecast revision. The daily abnormal return is calculated as the firm's return on day *t* minus the daily return of a benchmark portfolio with the same size decile as the firm.
$EF\_Rev_{i,j,t}$	= analyst forecast revision, calculated as the difference between the analyst's current annual earnings forecast and the same analyst's prior forecast, scaled by the stock price at the end of the month before the revision.
$Visit\_prev\_month_{i,j,t}$	= indicator variable for site visit. It equals 1 if analyst *i* visits firm *j* during the month before the current earnings forecast and 0 otherwise.
$Revenue\_Forecast_{i,j,t}$	= indicator variable for revenue forecast. It equals 1 if the earnings forecast is accompanied by a revenue forecast, and 0 otherwise.
$Horizon_{i,j,t}$	= forecast horizon, calculated as the number of calendar days between the forecast issuance date and the subsequent earnings announcement date.
$Numcom_{i,t}$	= firm coverage, calculated as the log transformation of the number of firms covered by analyst *i*.
$Numind_{i,t}$	= industry coverage, calculated as the log transformation of the number of CSRC Level-2 industries covered by analyst *i*.
$Brokersize_{i,t}$	= broker size, calculated as the number of analysts working for the brokerage firm with which analyst *i* is associated.
$Star_{i,t}$	= indicator variable for star analysts.
$Genexp_{i,t}$	= analyst's general experience, calculated as the log transformation of the time interval in years between analyst *i*'s first forecast in the CSMAR database and his/her current forecast at time *t*.
$FE_{i,j,t,}$	= forecast error, calculated as the absolute value of the difference between the actual earnings and analyst *i*'s forecast, scaled by the firm's stock price in the last year.
$MV_{j,t}$	= firm size, calculated as the log transformation of the market value of equity of firm *j* at the end of the last fiscal year.

TABLE 9 (Cont'd)

	Coeff. *(t-value)*
EF_Rev	0.2537***
	(6.26)
EF_Rev× Visit_prev_month	0.0448**
	(2.35)
Visit_ prev_month	0.0031***
	(3.54)
Revenue_Forecast	-0.0022
	(-1.07)
Horizon	-0.0003**
	(-2.19)
Numcom	-0.0015
	(-1.42)
Numind	0.0019
	(0.97)
Brokersize	-0.0003
	(-0.24)
Star	0.0040***
	(2.91)
Genexp	-0.0003
	(-0.36)
FE	0.2117***
	(8.29)
MV	-0.0003
	(-0.63)
Industry Fixed Effects	Yes
Observations	17,317
Adj. R^2	0.021

TABLE 10
Site visits and local advantage

This table presents the results from the following regression:

$$Rel\_Accuracy_{i,j,t} = \alpha + \beta_1 Non\_local_{i,j,t} + \beta_2 Visit\_Freq_{i,j,t} + \beta_3 Non\_local_{i,j,t} \times Visit\_Freq_{i,j,t} + \boldsymbol{\gamma}\ \boldsymbol{Controls} + \varepsilon_{i,j,t}$$

The full sample consists of 17,714 analyst forecasts issued from 2009 to 2012. As in Bae et al. (2008), the control variables are demeaned by firm-year averages. The t-values in brackets are based on standard errors adjusted for firm and year clustering. ***, **, and * indicate coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Variable definition:

$Rel\_Accuracy_{i,j,t}$	= analyst *i*'s relative forecast accuracy, measured as the difference between the forecast error of analyst *i* for firm *j*'s year *t* earnings and the average forecast error across all analyst forecasts of firm *j*'s year *t* earnings, divided by the average absolute forecast error across all analyst forecasts of firm *j*'s year *t* earnings, then multiplied by -1. A higher value implies a higher level of forecast accuracy. For each analyst, we calculate the forecast error by using this analyst's most recent annual earnings forecast issued in the year before the firm's earnings announcement.
$Non\_local_{i,j,t}$	= indicator variable for non-local analysts. It equals 1 for analyst *i* whose brokerage firm is more than 400 kilometers (250 miles) away from the headquarters of firm *j*, and 0 otherwise.
$Visit\_freq_{i,j,t}$	= site visit frequency, measured as the number of site visits conducted by analyst *i* in the six-month period before the issuance date of the current earnings forecast used to calculate the analyst's forecast accuracy, or the period between last year's earnings announcement date and the current earnings forecast issuance date, whichever period is longer. *Visit_freq* equals 2 (1, 0) if analyst *i* visited firm *j* two or more (once, zero) times during this period.
$Horizon_{i,j,t}$	= forecast horizon, calculated as the number of calendar days between the forecast issue date and corresponding earnings announcement dates.
$Firmexp_{i,j,t}$	= analyst's firm-specific experience, calculated as the log transformation of the time interval in years between analyst *i*'s first forecast for firm *j* and his/her forecast at time *t* for firm *j*.
$Genexp_{i,t}$	= analyst's general experience, calculated as the log transformation of the time interval in years between analyst *i*'s first forecast in the CSMAR database and his/her current forecast at time *t*.
$Brokersize_{i,t}$	= broker size, calculated as the number of analysts working for the brokerage firm with which analyst *i* is associated.
$Numind_{i,t}$	= industry coverage, calculated as the log transformation of the number of CSRC Level-2 industries analyst *i* covers.
$MV_{j,t}$	= firm size, calculated as the log transformation of the market value of equity of firm *j* at the end of last fiscal year.

TABLE 10 (Cont'd)

	Column (1) *Coeff.* *(t-value)*	Column (2) *Coeff.* *(t-value)*	Column (3) *Coeff.* *(t-value)*	Column (4) *Coeff.* *(t-value)*
Non_local	-0.0190***		-0.0168**	-0.0300***
	(-2.86)		(-2.39)	(-3.96)
Visit_freq		0.0364***	0.0359***	0.0108***
		(8.15)	(7.99)	(2.96)
Non_local×Visit_freq				0.0364***
				(5.24)
Horizon	-0.2734***	-0.2711***	-0.2711***	-0.2711***
	(-6.80)	(-6.71)	(-6.72)	(-6.71)
Firmexp	0.1450***	0.1429***	0.1424***	0.1424***
	(5.37)	(5.50)	(5.42)	(5.44)
Genexp	0.0147	0.0157	0.0152	0.0151
	(1.08)	(1.14)	(1.12)	(1.12)
Brokersize	0.0195	0.0161	0.0161	0.0158
	(0.73)	(0.60)	(0.60)	(0.59)
Numind	-0.0365	-0.0368	-0.0361	-0.0357
	(-1.20)	(-1.20)	(-1.18)	(-1.18)
MV	0.0096***	0.0093***	0.0098***	0.0097***
	(4.02)	(2.84)	(2.94)	(2.83)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,714	17,714	17,714	17,714
Adj. R^2	0.083	0.084	0.084	0.084

TABLE 11
Determinants of analyst site visits

This table reports the results from the following regression:

$$
\begin{aligned}
Visit\_firm_{i,j,t} = {} & \alpha + \beta_1 Distance_{i,j,t-1} \\
& + \beta_2 Brokersize_{i,t-1} + \beta_3 Manufacture_{j,t-1} + \beta_4 Tangibility_{j,t-1} + \beta_5 Concentration_{j,t-1} \\
& + \beta_6 StrongBuy_{i,j,t-1} + \beta_7 Disclosure\_rating_{j,t-1} + \beta_8 ANA_{j,t-1} + \beta_9 SOE_{j,t-1} + \beta_{10} MV_{j,t-1} \\
& + \beta_{11} ROA_{j,t-1} + \beta_{12} Age_{j,t-1} + \beta_{13} BM_{j,t-1} + \beta_{14} Debt_{j,t-1} + \varepsilon_{k,j,t}
\end{aligned}
$$

The full sample consists of 49,553 analyst-firm-year observations in the period of 2009 to 2012. The z-values are reported in parentheses and are based on standard errors adjusted for firm clustering. ***, **, * indicate the coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Please see Appendix B for the measurements of *Manufacture*, *Tangibility*, *Concentration*, *MV*, and *BM,* except that they are measured in year t-1. The measurements of other variables are as follows:

$Visit\_firm_{i,j,t}$	=	Indicator for site visit, 1 if analyst *i* visits firm *j* at least once in year *t*, and 0 otherwise.
$Distance_{i,j,t-1}$	=	The natural logarithm of the geographical distances (in kilometers) between analyst *i* and the visited firm *j*'s headquarters.
$Brokersize_{i,t-1}$	=	Broker size, defined as the natural logarithm of the number of analysts working for the brokers.
$StrongBuy_{i,j,t-1}$	=	An indicator variable that equals 1 when analyst *i* issue at least one strong-buy recommendation for firm *j* in year *t-1*.
$Disclosure\_rating_{j,t-1}$	=	Indicator for high disclosure rating, based on the rating of information disclosure quality assigned by the Shenzhen Stock Exchange to the listed companies, with four categories, A, B, C, and D. The indicator variable is equal to 1 if the disclosure rating for firm j in year t-1 is A or B, and 0 otherwise.
$ANA_{j,t-1}$	=	Analyst coverage, measured as the natural logarithm of one plus the total number of analysts issuing earnings forecasts in year *t-1*.
$SOE_{j,t-1}$	=	Indicator variable for SEO firms, 1 if firm *j* is a state-owned enterprise in year *t-1*, and 0 otherwise.
$ROA_{j,t-1}$	=	Return of assets, calculated as the net income divided by total assets of firm *j* in year *t-1*.
$Age_{j,t-1}$	=	Firm age, measured as the natural logarithm of 1 plus the number of years the company has been listed up to the end of fiscal year *t-1*.
$Debt_{j,t-1}$	=	The ratio of total debt divided by total assets in year t-1.

TABLE 11 (Cont'd)

	Coeff. *(z-value)*
Variables related to the cost of conducting site visits	
Distance	-0.1028***
	(-7.84)
Brokersize	0.5847***
	(5.38)
Variables related to the benefit of conducting site visits	
Manufacture	0.0715
	(1.64)
Tangibility	0.0770***
	(2.77)
Concentration	0.0576***
	(2.84)
Control variables	
StrongBuy	0.1328*
	(1.87)
Disclosure_rating	0.1664***
	(4.38)
ANA	0.1809***
	(9.77)
SOE	-0.2576***
	(-6.79)
MV	0.0059
	(0.20)
ROA	-0.3379
	(-1.15)
Age	0.0423***
	(7.74)
BM	0.1069
	(1.43)
Debt	0.0108
	(0.11)
Industry Fixed Effects	Yes
Observations	49,553
Pesudo-R^2	0.0434