1-2014

Seeing is Believing: Do Analysts Benefit from Site Visits

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This version: January 2014

ABSTRACT: Using the unique data of analysts' site visits to Chinese listed companies, we examine whether and how analysts' site visits help improve their forecast performance. We find that the forecast accuracy of analysts improves after they visit the target firms and this improvement still holds after controlling for the concurrent change in the forecast accuracy of analysts who do not conduct site visits. Such an improvement is more pronounced for firms with better corporate governance; for more experienced analysts; and for firms with higher earnings volatility. Moreover, the improvement of forecast accuracy is less pronounced when current site visits are preempted by preceding site visits, and when there are other non-analyst visitors. Furthermore, we find that local analysts benefit more from corporate site visits than non-local analysts. Lastly, we document a larger market reaction to earnings forecasts issued by visiting analysts than those issued by non-visiting analysts.

Keywords: Site visits, analysts, select access, forecast accuracy, market reaction.
Data Availability: Data are publicly available.

* We greatly appreciate the helpful comments and suggestions from Shuping Chen, Mark DeFond, Ole-Kristian Hope, and conference participants at the 2013 Alumni Symposium of USC Leventhal School of Accounting (Aug 2013) and workshop participants at the University of Hong Kong (Oct 2013). Please contact authors at qcheng@smu.edu.sg (Qiang Cheng), feidu@hku.hk (Fei Du), wangxacy@hku.hk (Xin Wang), and wangyutao@cufe.edu.cn (Yutao Wang). We gratefully acknowledge the financial support from the General Research Fund of Hong Kong Research Grants Council (project No. 790613).

1 Introduction

In this study, we investigate whether financial analysts gain information advantage from a specific type of information acquisition activities, analysts' corporate site visits to listed companies. This investigation directly answers the call for research on penetrating the "black box" of analyst work process (Call et al. 2013). The motivation for our research question is two-fold. First, although financial analysts are important information intermediaries in the capital markets, it is not well understood how exactly analysts benefit from their information acquisition activities. Such a lack of knowledge is primarily due to the lack of data on analysts' information acquisition activities. Prior research generally uses indirect proxy for analysts' information acquisition efforts such as the forecast frequency and the number of firms followed by an analyst (Jacob et al. 1999). Recently, some studies use analysts' activities to identify information advantage possessed by certain analysts. For example, recent studies by(Green et al. 2012) and (Mayew et al. 2013) find that analysts who host investor conferences or ask questions in conference calls possess superior information. However, such evidence is indirect and is subject to alternative explanations. After all, there are many other analysts in the investor conferences and conference calls and every participant should benefit from managers' discussions. Thus, it is unclear that the source of superior information is attributable to some analysts' activities in these conferences. In addition, it is likely that analysts with superior information are more likely to host conferences and ask questions in conferences. In this paper, we study analysts' corporate site visits and they better capture analysts' information acquisition activities.

Second, Regulation Fair Disclosure (Reg. FD) prohibits selective disclosure and as a result, financial analysts cannot rely on personal relationship to obtain information from the management in the post Reg FD period (Chen and Matsumoto 2006; Cohen et al. 2010). As a

result, selective access has become more and more important for financial analysts to acquire information. There is very limited evidence regarding how selective access influences market professionals, and it remains underexplored in the literature how selective access events affect analysts' information advantage (Bushee et al. 2011; Green et al. 2012). Selective access is defined as the opportunity for analysts to meet privately with management in individual or small group settings (Bushee et al. 2011). Typical selective access events include one-on-one meetings at investor conferences (Bushee et al. 2011) and corporate site visits to company headquarters and manufacturing facilities (Cheng et al. 2013).[2] To date, there is no empirical evidence regarding how site visits can benefit analysts in their research. This is surprising given the increasing importance of corporate site visits. As indicated in the 2012 All-Europe Research Survey, a site visit is an important type of information acquisition activity.[3] Two recent papers document that site visits convey useful information into the capital market (Solomon and Soltes 2013; Cheng et al. 2013). However, the mechanism through which the information is incorporated into the capital markets is unclear. This study aims to complement these studies by examining the relationship between site visits and analysts' information advantage.

The lack of research in this area is mainly due to the lack of data. In the U.S., site visits data are not available: firms either do not maintain archival records of site visits, or they prohibit distributing such information (e.g., Soltes 2012). The research opportunities emerged in China recently. Since 2009, the China's Shenzhen Stock Exchange (SZSE) has required the listed companies to disclose the information on investors' site visits in the annual reports, including visit dates, the names of visiting institutions, and the contents of discussion during site visits.

[2] In the SEC round table discussion on Reg. FD, Chairman Harvey Pitt commented that companies should still allow site visits such that investors can visit their headquarters or plants and ask operating managers questions.
[3] This survey shows that among the 12 types of popular information acquisition activities, investors rank corporate site visits (ranked No. 6) higher than one-on-one meetings with the management (No. 7), analysts' written reports (No. 8), and analysts' earnings estimates (No. 12).

This mandatory disclosure requirement provides us with a unique setting to test how analysts benefit from their corporate site visits. While acknowledging that institutional differences between China and the U.S. may limit the generalizability of our findings to the U.S., we want to point out that China has followed the U.S. version of Reg. FD by mandating that if an issuer discloses material nonpublic information to certain enumerated persons, it must make public disclosure of that information.[4] Also, our findings in the Chinese context are important in their own right given China's increasingly important role in the world economy.

Analysts are likely to gain new, credible information about a firm through their corporate site visits to this firm because they are able to view this firm's fixed assets, look over its inventory warehouses, observe its operating and R&D activities, and talk to middle- or low-level employees. The obtained information is credible because it is difficult for the firm to hide or fake real corporate activities and assets. Thus, we hypothesize that visiting analysts obtain information advantage through site visits. Specifically, we conjecture that the forecast accuracy of visiting analysts improves after their site visits. However, it is possible that visiting analysts might not receive any useful information. Site visits might be corporate events for public relations or entertainment purposes. Furthermore, visitors usually do not meet with top managers during site visits.[5] Therefore, if the top managers are the only reliable source of information, visitors will not gain any useful information. Thus, it remains an empirical question on whether site visits are correlated with superior analyst forecast performance.

To examine our conjecture that corporate site visits are correlated with improved forecast

[4] According to the Article 41 of the CSRC's Reg FD, which was effective on January 31, 2007, "A listed company shall, holding conference calls, analysts' meetings, road shows, accepting investors' field investigation, etc., communicate with the institutions and individuals in respect of the business operations, financial status and other events, but it shall not provide any inside information."

[5] According to many corporate site visit policies that we went through, board secretaries or securities affairs representatives are usually the liaison persons for site visits and they are responsible for approving site visit applications, organizing the field tours, and accompanying the visitors during the entire site visit.

accuracy, we adopt a difference-in-difference research approach using the non-visiting analysts' forecast accuracy as the control for the possible concurrent factors which affect all analysts' forecast performance for the same firm. Such a research design also helps to mitigate the concern that some firm characteristics are omitted correlated variables. Specifically, we utilize the visitors' names as disclosed for every site visit to a firm and classify the analysts following this firm as two groups for such a site visit event: the group of visiting analysts from the brokers whose names are identified as visitors; and the group of non-visiting analysts who follow the same firm but their brokers' names are not on the visitors' list. For each group of analysts, we calculate the average analyst forecast accuracy in the pre-visit period and also the post-visit period. Then, we calculate the change in forecast accuracy for these two analyst groups around each site visit and use it as the main variable for our regressions (i.e., for every site visit, we have two observations of forecast accuracy improvement; one for visiting analysts and the other for non-visiting analysts). According to our main research hypothesis, we expect to see an improvement in forecast accuracy of visiting analysts after controlling for the concurrent change in non-visiting analysts' forecast accuracy.

Our sample consists of 4,947 site visits occurring in 1,437 firm-years of 845 unique firms during 2009-2012, after requiring the earnings forecasts issued by both visiting and non-visiting analysts. Consistent with our hypothesis, we document improved forecast accuracy (i.e., decreased absolute forecast errors) in the post-site-visit period for visiting analysts, even after controlling for the change in non-visiting analysts' forecast accuracy around the site visits. To provide additional insights on the information role of site visits, we conduct cross-sectional analyses for several factors which are expected to influence the costs and benefits of paying a site visit to a firm. First, the information advantage of visiting analysts should be more

pronounced when the cost of acquiring new information during the site visit is lower. We expect that well-governed companies are more open to visitors' questions and are less likely to hide information or even provide misleading information during the site visits, which reduces information acquisition costs. Using board independence and the CEO-Chairman duality to measure corporate governance, we find stronger improvement in visiting analysts' forecast accuracy for firms with better corporate governance. In the second cross-section analysis, we examine whether visiting analysts' forecast accuracy improves more when these analysts possess a longer firm-specific experience. We conjecture that visiting analysts with a longer experience have a lower information processing cost and hence obtain a more pronounced information advantage through site visits. The results are consistent with our conjecture.

The expected benefit of site visits are expected to be correlated with the existing information uncertainty for firms' performance and also with the richness of the information content during site visits. Specifically, when a firm's earnings performance is more volatile (proxied for by the standard deviation of earnings), the information obtained from site visits will be more useful for earnings forecasts. In the third cross-sectional analysis, we show consistent evidence that visiting analysts have a greater improvement in forecast accuracy relative to that of non-visiting analysts for firms with higher standard deviation of net income. In the fourth cross-sectional analysis, we measure the information richness of site visits as the market share of the visited firms. By visiting the leading firms in an industry, analysts acquire not only firm-specific information but also the knowledge of the industry trend and/or the macroeconomic development. Such industry- and market-wide knowledge is important for analysts to make firm-specific earnings forecasts. Our results show that visiting analysts enjoy a more pronounced information advantage by visiting firms with larger market shares.

Furthermore, we expect that site visits are less likely to bring information advantage to visiting analysts when such site visits are preceded by any recent site visits by other investors, or when such site visits are not exclusive to visiting analysts (i.e., there are other visitors, mainly fund managers, in the same site visit trip as visiting analysts). In our fifth cross-sectional analysis, the empirical results support this expectation.

One concern with our analyses is that whether the category of visiting analysts is merely the category of analysts who are geographically close to visited firms, given that prior studies document a higher likelihood of analysts visiting firms closer to their offices (Cheng et al. 2013) and that geographic proximity is documented as one determinant for the *level* of forecast accuracy (Bae et al. 2008). First, in our research design we examine the *change* in forecast accuracy around site visits and hence to a large extent we control for the fixed effect of geographic proximity on forecast accuracy. Second, we further address this concern by including geographic distance in our regressions. We find no significant results for geographic distance while the effects of site visit still exist. Interestingly, using the interaction item between site visit indicator and analysts' geographic distance, we show that analysts benefit more from their site visits to firms located closer to their offices.

Lastly, we examine the market reaction to earnings forecasts. Our evidence show that the three-day absolute abnormal stock returns around earnings forecasts are greater for visiting analysts than for non-visiting analysts. This evidence lends credence to our results based on analysts' forecast accuracy.

This study contributes to the literature in several important ways. First, it provides 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 analysts'

forecast performance, including industry specialization (Jacob et al. 1999), firm-specific experience (Mikhail et al. 1997), superior access to management (Green et al. 2012; Soltes 2012), geographic proximity (Malloy 2005), and educational ties (Cohen et al. 2010). These studies focus more on analysts' attributes-who they are, and less on what they do. However, the challenge of directly observing and measuring the effect of analysts' information acquisition activities, partly due to the confidential nature of these activities, hinders researchers' abilities to investigate the role of information acquisition activities in analysts' forecast performance. Note that better forecast performance might come from analysts' better skills in processing common information, not necessarily from analysts' additional information acquisition activities. We take advantage of the mandatory disclosure of analysts' corporate site visits in China and examine how such site visits can provide visiting analysts with an information advantage.

Second, this study is related to a growing literature that examines how selective access to managers influences analysts' performance. Two recent working papers show that private interactions with CEOs/CFOs can lead to analysts' information advantage in the post Reg. FD era (Green et al. 2012; Soltes 2012). Complementing these studies, we provide evidence that in the absence of top executives as usually during site visits, analysts still obtain relevant information cues that help to improve forecast accuracy. In addition, compared with other selective access events, such as investor conferences, site visits are less contaminated by potential selective disclosure due to the usual absence of top executives during site visits.

Third, our study contributes to the analyst forecast literature with respect to geographic proximity being a determinant of earnings forecast accuracy. Our study sheds light on the mechanism through which geographic proximity leads to information advantage. Prior studies show that local analysts issue more accurate forecasts than remote analysts, and this effect is

robust after controlling for the effects of common language and social ties among local people (Malloy(2005); (Bae et al. 2008). Our studies extend this literature by showing that the benefit of site visits for analyst forecast accuracy is more pronounced with the geographic proximity between analysts and visited firms. Combined with the finding in prior studies that analysts are more likely to visit firms with a short geographic distance (Cheng et al. 2013), our study indicates how site visits serve as a mechanism through which local analysts can obtain the information advantage relative to non-local analysts for a listed firm.

The remainder of this paper proceeds as follows. Section 2 presents the development of research hypotheses. Section 3 describes the sample and the empirical research design. Section 4 reports the results from main analyses and Section 5 additional analyses. Section 6 concludes.

2 Prior Literature and Hypothesis Development

2.1 Analysts' information acquisition and forecast performance

Analysts are important capital market intermediaries that help reduce information asymmetry between companies and outside investors (e.g., O Brien and Bhushan 1990). Analysts' superior forecast performance generally arises from these analysts' active information acquisition and outstanding information processing skills. Prior literature has examined the effect of analysts' efforts on their forecast performance but these studies usually rely on indirect proxies of information acquisition, such as industry specialization (Jacob et al. 1999) (Jacob et al. 1999), firm-specific experience (Mikhail et al. 1997), and brokerage firm size(Clement 1999; Jacob et al. 1999). As a result, there is little direct evidence on how analysts' information acquisition activities affect their forecast performance. Two recent studies find that analysts' superior information is associated with their activities including hosting investor conferences

(Green et al. 2012) and asking questions in conference calls (Mayew et al. 2013). Since most analysts can attend these conference events which are not selective, other non-hosting or silent analysts should also collect the information in the same events and benefit from the information disclosed during the conferences. Therefore, the indicators of hosting conferences or asking questions might not reflect a higher level of information collecting activities in the conference events but could be good indicators for these analysts' superior information access in a general situation.

In other words, the effect of information acquisition activities is better captured by *analyst-specific* activities, not by analysts' activities as a herd (i.e., all analysts' activities at the same moment). Anecdotally, analysts actively engage in information acquisition activities through their visiting companies on site. A typical analyst hosts around one field trip per month in a medium-sized full-service broker-dealer (Groysberg et al. 2011). These field trips are analyst-specific efforts (i.e., it is clear that non-visiting analysts do not expend efforts on collecting information on site at the same moment) and thus the comparison between visiting and non-visiting analysts provides a better setting to examine analysts' information acquisition activities.

2.2 Corporate site visits and visiting analysts' information advantage

Reg FD prohibits executives from selectively disclosing material nonpublic information to market professionals or institutional investors. Reg. FD was implemented to address the public concern that managers provide material information to select investors, who then trade profitably at the expense of less informed investors. Prior studies show that Reg. FD achieves this goal of curtailing the selective disclosures. Specifically, the implementation of Reg. FD is associated with a shift toward a richer public information environment (Bailey et al. 2003; Heflin et al. 2003)

and a decrease in the informativeness of analysts' reports (Gintschel and Markov 2004; Irani and Karamanou 2003; Mohanram and Sunder 2006). In the post Reg. FD period, the information leakage is curtailed in the period prior to management earnings forecasts (Kothari et al. 2009; Sinha and Gadarowski 2010), in the quarter before a break in a string of earnings increases (Ke et al. 2008), and in the closed conference calls after earnings announcements (Bushee et al. 2004). As a result, analysts have to rely more on other means to obtain information, including their corporate site visits.

We argue that analysts benefit from corporate site visits for the following reasons. First, analysts are able to observe firms' operations; as the old adage goes, "seeing is believing." During site visits, analysts can observe the productivity level of a company and ask questions about operation details, which is above and beyond a passive acceptance of whatever the company reports in the MD&A section of the annual reports. In addition, it is relatively easier for managers to manipulate the accounting numbers in the annual reports, but much more difficult for managers to fake real activities and assets such as manufacturing assemblies, loaded delivery trucks, and busy sales representatives. Therefore, through site visits analysts obtain credible information cues that are useful for them to conduct mosaic analysis and issue more accurate forecasts. Second, analysts have to spend resources and efforts on their activities of corporate site visits. Based on the fact that every year there are many site visits conducted by financial analysts who are assumed to be rational, we believe that benefits from site visits should outweigh the costs. Specifically, analysts should experience an improvement in their forecasts accuracy by visiting the target firms and such an improvement should be greater than that for non-visiting analysts. Otherwise, the site visit costs paid by visiting analysts would not be well justified. In summary, we predict a positive relationship between site visits and forecast accuracy. Our first

hypothesis is formally stated as follows:

H1: The forecast accuracy of visiting analysts improves more after site visits when compared to that of non-visiting analysts.

However, we might not find results consistent with H1 because site visits might not be useful for making accurate earnings forecasts. Investors' site visits are usually organized by the company and led by the board secretary. It is unclear whether the company has a full control over the information flows during the site visits and hence it is possible that analysts rely too much on the information conveyed from the organizers rather than discover new information actively by themselves. In other words, visiting analysts might not obtain new information or even get misleading information fed by the organizers. Thus, it remains an empirical question whether the site visits are useful for forecast accuracy as stated in H1.

The effectiveness of site visits for analyst forecast accuracy likely varies with some characteristics of visited firms, visiting analysts, and site visits. First, the usefulness of site visits is greater when the costs are lower for acquiring and processing information during site visits. As for the information acquisition cost, prior studies show that firms with better corporate governance are more transparent in disclosing firm-specific information by issuing management forecasts more frequently and precisely (Eng and Mak 2003) (Ajinkya et al. 2005; Karamanou and Vafeas 2005). Moreover, well-governed firms are less likely to commit financial frauds (Beasley 1996) and are less likely to manipulate earnings numbers (Dechow et al. 1996). It thus follows that during the site visits to firms with better governance, the corporate executives are less likely to prevent analysts from discovering new information and also less likely to provide analysts with misleading earnings information. Therefore, during site visits to firms with better corporate governance, visiting analysts face a lower information acquisition cost and are expected to possess a larger information advantage over non-visiting analysts.

The usefulness of site visits also depends on analysts' skills to process the information obtained from their site visits. We conjecture that experienced analysts are better at processing and understanding the information from site visits. Therefore, visiting analysts are expected to obtain a more pronounced information advantage when these analysts have more firm-specific experience for the visited firms. These arguments lead to our hypothesis:

H2: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is more pronounced for visited firms with better corporate governance.

H3: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is more pronounced for more experienced visiting analysts.

Next, the information advantage of visiting analysts is expected to be more pronounced for those site visits with higher expected benefits. First, site visits to firms with volatile earnings should provide a greater benefit in reducing information uncertainty, and thus help visiting analysts to achieve a greater information advantage. A higher level of earnings volatility means less stable and less predictable operations, making it more difficult to make accurate earnings forecasts. Therefore, new information obtained from site visits is more valuable for earnings forecasts for firms with more volatile earnings performance. In addition, firms with higher earnings volatility make fewer voluntary disclosures (Waymire 1985), which constrains the information sources available for analysts. After all, analysts' forecast accuracy is positively correlated with firm's disclosure level (Chang et al. 2000; Hope 2003). When facing constrained information sources for firms with higher uncertainty of earnings performance, analysts are expected to benefit more from their site visits.

The second situation where site visits provide a great benefit is when visiting a firm with a leading position in the industry. Specifically, we conjecture that the market shares of the visited firms have a positive impact on the information role of corporate site visits. By visiting a firm

with a higher market share, the visiting analysts not only know firm-specific information, but also industry-wide or market-wide knowledge. In other words, site visits to industry-leading firms provides richer information content than other site visits. Such a richer information content, mainly industry or market knowledge, is expected to be useful for analysts to make more accurate earnings forecasts. This expectation is based on the important role of analysts' industry knowledge in their forecast performance, as documented in prior studies that industry knowledge helps analysts better process information (Piotroski and Roulstone 2004), and that analysts make more accurate forecasts when target firms' operations are more synchronous with industry trend (Hutton et al. 2012). We formally state our hypotheses as follows:

H4: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is more pronounced for visited firms with more volatile earnings.

H5: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is more pronounced for visited firms with greater market shares.

Lastly, we expect the benefits of site visits are contingent on the timing and the participants of site visits. As for the timing of site visits, we conjecture that site visits are less beneficial if these visits are conducted in a short time interval after any other investors' site visits to the same firm. Such visits preceded by other site visit events should be less informative since managers may simply repeat the same information disclosed in the preceding site visits. The possibly pre-empted information content makes the site visits less useful if these site visits follow any other site visit in a short period.

As for the participants of a site visit tour, we take advantage of the mandatory disclosure of visitors' names for site visits and identify other non-analyst visitors who visit the same firm with analysts. The existence of other non-analyst visitors, especially buy-side fund managers, will make the new information during site visit less exclusive to visiting analysts, and hence weakens

the usefulness of site visits for visiting analysts to gain the information advantage. Specifically, other site visitors, such as fund managers, could spread out the information obtained from site visits through their direct trading activities or their communication with other parties who do not visit the firm. In this way, other market participants, including non-visiting analysts, get to know the new information obtained during site visits. Therefore, visiting analysts are expected to have a smaller information advantage over non-visiting analysts, if the site visits are conducted with other market participants (i.e., not just visiting analysts on the same field trip). In summary, we have the following hypotheses:

H6: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is less pronounced for site visits preceded by other visits.

H7: The forecast accuracy improvement of visiting analysts compared with non-visiting analysts is less pronounced for site visits with other non-analyst visitors.

3 Sample and Methodology

3.1 Sample

Data on analysts' site visits are available in China for recent years. According to the Shenzhen Stock Exchange (SZSE) Information Fair Disclosure Guidelines, effective from August 2006, firms listed on the SZSE have to report to the China Securities Regulation Committee (CSRC) two working days before site visits conducted by institutional investors, financial analysts, mutual fund managers, banks and other visitors. After the site visit, the firm has to provide a summary of the site visit to both the CSRC and the SZSE. 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.[6] Appendix A provides an example showing that brokers have field trips to a firm's headquarters, operating facilities, and warehouses.

We hand-collect the site visit records in the annual reports of the firms listed on the SZSE for the period of 2009 -2012. Our data include the event dates and the names of the visiting institutions. We identify the site visits involved with at least one broker and exclude those conducted by other types of visiting institutions such as mutual funds and banks.[7] This step leads to a total of 18,078 visits, with the yearly number increasing from 2,233 in 2009 to 7,303 in 2012. The dramatic increase in the frequency of site visits is consistent with the findings in Cheng et al. (2013) who document an increased prevalence of site visits conducted by all types of investors in China market from 2009 to 2011.[8]

We impose additional data restrictions to obtain the final sample. We require the availability of analysts' annual EPS forecasts for the coming year within the six-month period prior to site visits. Such a requirement of pre-site visit forecasts is necessary for us to calculate the change of forecast accuracy between pre- and post-site visit periods. In addition, there are some site visits with adjacent event dates to each other. We combine every two site visits with adjacent dates as one site visit. Next, we delete firms in financial industries and firms with missing values of actual EPS or stock prices for the calculation of analyst forecast errors. After these procedures, we have a remaining sample of 15,496 analysts' site visits.

Following our research design of difference-in-difference method, we further impose two data screening procedures which cause the major loss of site visit observations. First, we require

[6] The disclosure of site visits is strictly enforced. The SZSE publicly denounced a few companies that failed to disclose site visit information with the SZSE.
[7] Note that when we code the two visit characteristics variables, the number of preceding visits, and the indicator of group visits, it is based on the entire site visit database, not constrained to those visits conducted by analysts.
[8] There are a large number of IPO firms in 2011. The larger sample of listed firms also contributes to the large increase in the frequency of analysts' site visits in 2012.

the earnings forecasts made by visiting analysts in the whole window around site visits (i.e., six months prior to site visit dates until one month after site visits).[9] Without visiting analysts' forecasts, we cannot measure their forecast accuracy. Such requirement results in the exclusion of 8,014 analysts' site visits. The fact that almost a half of the analysts' site visits are excluded suggests that there are many site visits where visiting analysts do not make any forecasts around the site visits. Second, to perform the measurement of accuracy improvement, we further require at least one forecast made by visiting analysts in the pre-site visit period.[10] This procedure leads to an additional deduction of 2,394 site visits where visiting analysts make forecast only in the post-visit period but none for pre-visit period. Lastly, we impose the same requirement, the availability of earnings forecast in the pre-visit period for non-visiting analysts. The final sample consists of 4,947 site visits for which we have the data for visiting and non-visiting analysts' forecast accuracy in both the pre- and post-site visit period. These site visits occur in 1,437 firm-years for 845 unique firms during 2009-2012. As described in the following sections, we calculate the forecast accuracy for the group of visiting and non-visiting analysts, respectively, and then use the change in forecast accuracy for these two groups for each site visit event as the dependent variable in our regressions. Therefore, for each of 4,947 site visits, we have two observations of analyst forecast performance improvement (one for visiting analysts and the other for non-visiting analysts), leading to a total of 9,894 observations of analyst performance. Table 1 summarizes the sample selection procedure.

[Table 1 about here]

3.2 Empirical Design

[9] We match analysts' broker firms in analyst forecast database with the brokers' names in the site visit database. One broker usually has one analyst covering a specific firm. Thus, we use broker and analyst interchangeably when discussing forecasts.

[10] Specifically, if an analyst does not issue new forecasts in the post-event period, we will use this analyst's earnings forecasts in the pre-event period as the forecasts during the post-event period.

Our first set of tests investigates whether the forecast accuracy of visiting analysts improves more relative to that of non-visiting analysts. For this purpose, we estimate the following model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

Where, $\Delta AFE_{k,j,t} = -(Post\_Visit\_AFE_{k,j,t} - Pre\_Visit\_AFE_{k,j,t})$ with *k*= visiting or non-visiting analyst groups for the site visit occurring at day t to firm *j*. This variable captures the change in forecast accuracy for analyst group *k* from six months before site visit to one month after site visit. More specifically, for each analyst group, we first calculate the mean or median of every analyst's most recent annual EPS forecasts prior to site visit as the consensus forecast of this group, and then calculate the pre-site visit absolute forecast errors for this group (i.e., *Pre_Visit_AFE*). The forecast error is measured as the difference between consensus forecast and actual EPS, scaled by stock price at the beginning of the firm-year. Similarly, we identify the most recent forecasts made by the same group of analysts prior to the one month after site visits, calculate their forecast consensus and develop the absolute forecast error for the same group in the post-site visit period (i.e., *Post_Visit_AFE*). Then, we use the difference in forecast accuracy between post-site visit and pre-site visit periods (ΔAFE) as the dependent variable.

We add a negative sign to the difference as shown in the formula. In this way, a positive value of the dependent variable proxies for an improvement in the forecast accuracy. For each site visit, we have two observations of ΔAFE, one for the visiting analysts group and the other for non-visiting analysts group. Note that according to our definition, if the visiting (or non-visiting) analysts do not update their forecasts in the post-event period (i.e., one month after site

visit), the post-site visit forecast consensus will be the same as pre-site visit forecast consensus, and hence we will document a zero change in forecast accuracy of this group of analysts.

The main variable of interest is the indicator variable for visiting analysts, $Visit_{k,j,t}$. It equals 1 if the group of analysts consists of those from the visiting brokers as recorded in the name of visitors for the site visit event at day t (i.e., when *k*= visiting), and zero otherwise (i.e., when *k*=non-visiting).

We control for variables which affect analysts' forecast accuracy as suggested by prior studies. Forecasts issued closer to the earnings announcement dates are generally more accurate than earlier forecasts (Clement 1999). As a result, we control for the change in forecast horizon (*ΔHorizon*), measured as the natural logarithm of the difference in the forecasting horizon (the number of days) of individual earnings forecasts made by this group of analysts (visiting group or non-visiting group) from the pre-visit to the post-visit period. In addition, more experienced analysts' forecasts are more accurate (Mikhail et al. 1997), and thus we control for analysts' firm-specific experience (*Firmexp*), measured as the natural logarithm of the average firm-specific experience (the number of years) of all analysts in analyst group *k* for firm *j*.[11] Moreover, prior research finds that forecasts issued by analysts from larger brokers are more accurate because large brokers have more resources. We thus control for broker size (*Brokersize*), defined as the average broker firms' size for analysts of group *k* and the broker firms' size is the number of unique financial analysts working for the broker firms in this firm-year. Furthermore, as suggested by prior literature, the forecast consensus of a larger group of analysts is more accurate. Thus we control for the number of analysts in each group of visiting or non-visiting analysts (*NumANA*). Lastly, we also add industry fixed effects to the regression models and report t-

[11] When we use overall experience (*Genexp*), calculated as the natural logarithm of the number of years since this analyst issued his/her first forecast. Results are similar.

values based on two-way clustered standard errors by firm and year.[12] Appendix B provides more detailed variable definitions.

4 Results

4.1 Univariate tests

Table 2 reports the descriptive statistics of the sample characteristics, separately, for visiting and non-visiting observations. We observe significant differences in the forecast accuracy changes between these two groups. Specifically, when using mean forecasts for the group forecast consensus, we document an improvement of 0.0252 in non-visiting analysts' forecast accuracy. As described in last section, we define ΔAFE as the difference in absolute forecast errors between the post-site visit and pre-site visit periods with a negative sign added. Hence, a positive value of ΔAFE implies a smaller absolute forecast error for the post-site visit period and the improved forecast accuracy. On the other hand, the improvement in visiting analysts' forecast is even greater at 0.0574, which is statistically significantly higher than that of non-visiting analysts (t=8.38). The results are similar when comparing the forecast accuracy based on the median value of individual forecasts as the forecast consensus of the group (t=8.87). Therefore, the univariate analysis shows that visiting analysts experience a greater improvement in their forecast accuracy when compared with that for non-visiting analysts.

However, one should interpret the univariate results with caution because we find that these two groups are also significantly different in other dimensions. Compared to forecasts issued by non-visiting analysts, forecasts issued by visiting analysts after site visits are closer to forecasts issued by visiting analysts before site visits as shown by the smaller change in the horizon for visiting analysts than that for non-visiting analysts (85.67 vs. 98.03 days), suggesting that

[12] We also estimate all regression models using firm fixed effects. Results remain the same.

visiting analysts are more likely to update their forecasts than non-visiting analysts.[13] Also, visiting analysts are more experienced and are from larger brokers. As shown in Table 3, the two groups of analysts are different in all dimensions, suggesting the importance of controlling for other analyst and forecast characteristics in the multivariate regressions.

[Table 2 about here]

4.2 Multivariate tests

Table 3 reports multiple regression results. Note that the reported t-values are based on standard errors adjusted for firm-level clustering. As reported in the table, we find that the coefficient on *Visit* is significantly positive for both dependent variables of *ΔAFE_Mean* (t=16.01) in column (1) and *ΔAFE_Median* (t = 14.55) in column (2). Again, according to the definition of *ΔAFE* in last section, the higher value of *ΔAFE* suggests a higher level of forecast accuracy since we add a negative sign to the difference in absolute forecast errors when defining the dependent variable. Therefore, the regression results suggest that visiting analysts improve more in terms of forecast accuracy in the periods around site visits than non-visiting analysts following the same firm. This finding supports H1 that analysts obtain useful information and gain an information advantage through their site visits to listed firms.

The coefficients of control variables are in line with prior literature. The coefficient on *ΔHorizon* is positive for both specifications, implying that the post-event forecasts are more accurate than the pre-event forecasts with a larger gap in timing (i.e., post-event forecasts are made at a time closer to earnings announcements). Firm specific experience is also significantly positively associated with forecast accuracy improvement (coefficient=0.0148 and 0.0134,

[13] We find that visiting analysts update their forecasts more often than non-visiting analysts when using the firm-constant control accuracy measure (untabulated). In that design we divide all analysts following firm j in the current year into two groups, a visiting group with analysts who visited firm j in the prior year and a non-visiting group with analysts who did not visit firm j in the prior year. We compare the forecast frequency of the visiting group and the non-visiting group for the same firm.

respectively), which is consistent with the findings in Mikhail et al.(1997). We also find a positive coefficient on the number of analysts (*NumANA*) which suggests a more pronounced improvement in forecast accuracy for a larger group of visiting or non-visiting analysts. However, the results of negative coefficients on brokerage house size (*Brokersize*) are not consistent with our expectation. Specifically, the negative coefficients suggest that with more analysts from larger brokers in the visiting or non-visiting groups, this group experiences a smaller improvement in analysts' forecast accuracy in the post-site visit period.

[Table 3 about here]

4.3 Cross-sectional analyses

In this section, we report tests of H2-H7. To test how corporate governance influences the role of site visits, we use the two measures of corporate governance, board independence and CEO-Chairman duality indicator, and their interaction with visiting indicator in the regressions.

$$\begin{aligned}\Delta AFE_{k,j,t} = \alpha &+ \beta_1 Visit_{k,j,t} + \beta_2 Dual_{j,t} + \beta_3 Visit_{k,j,t} * Dual_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} \\ &+ \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} \\ &+ Industry_{j,t} + \varepsilon_{k,j,t}\end{aligned}$$

$$\begin{aligned}\Delta AFE_{k,j,t} = \alpha &+ \beta_1 Visit_{k,j,t} + \beta_2 Indep_{j,t} + \beta_3 Visit_{k,j,t} * Indep_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} \\ &+ \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} \\ &+ Industry_{j,t} + \varepsilon_{k,j,t}\end{aligned}$$

The coefficient on the interaction term, β_3, captures the impact of corporate governance on the usefulness of site visits for analysts' forecast performance.

As shown in Table 4, the coefficient on interaction item, β_3, is significantly negative for firms with CEO-Chairman duality (i.e., poor corporate governance) but positive for board independence (i.e., good corporate governance). Combined together, these results indicate that by conducting site visits to well-governed firms, analysts experience greater improvement in forecast accuracy. Thus, H2 is supported.

[Table 4 about here]

To test how analyst experience affects the role of site visits, we construct an analyst experience indicator that equals one when the average firm-specific experience of all analysts in analyst group k for firm j is greater than the sample median. Note that for this test, we use an indicator for firm-specific experience as the control variable (*Firmexp*):

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Firmexp_{k,j,t} + \beta_3 Visit_{k,j,t} * Firmexp_{k,j,t} + \gamma_1 Horizon_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The coefficient on the interaction term, β_3, captures the impact of analyst experience on the usefulness of site visits for analysts' forecast accuracy. Table 5 presents the regression results. As hypothesized in H3, the coefficient on the interaction term, β_3, is significantly positive for both specifications (t=1.83 and 3.57, respectively). Therefore, more experienced analysts are better at taking advantage of the information obtained from site visits and experience larger improvement in forecast accuracy. Our H3 is supported.

[Table 5 about here]

Table 6 reports the results for H4. We measure the uncertainty of earnings performance as the standard deviation of net income for firm *j* in the past five years.[14] We then add the earnings volatility and its interaction with the site visit indicator to the model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 NI\_std_{j,t} + \beta_3 Visit_{k,j,t} * NI\_std_{j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The coefficient, β_3, is positive and significant at the 0.01 level as shown in columns (1) and (2). This indicates that site visits to highly volatile firms are more beneficial for analysts, consistent with H4.

[14] We use an alternative measure of CEO duality measured as the indicator variable that equals to 1 when a CEO for firm j serves as the chairman of the board in year t, and 0 otherwise. Results are the same.

[Table 6 about here]

We then add the market share and its interaction with the site visit indicator to the model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 MSHARE_{j,t} + \beta_3 Visit_{k,j,t} * MSHARE_{j,t} + \gamma_1 Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The columns (3) and (4) of Table 6 show a positive coefficient on the interaction item (t=2.46 and 2.95, respectively). These results indicate that analysts benefit more by conducting site visits to firms with larger market shares. Hence, our H5 is supported.

Lastly, we develop the number of preceding site visits within one month prior to current site visit (*Preceding_visits*); and the indicator for site visits without other non-analyst visitors (*Pure*); and their interaction with site visit indicator in the model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Pure_{j,t} + \beta_3 Visit_{k,j,t} * Pure_{j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Preceding\_visits_{j,t} + \beta_3 Visit_{k,j,t} * Preceding\_visits_{j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

As shown in Table 7, the coefficient β_3 is positive for regressions using the indicator for site visits conducted by only visiting analysts; and negative for regressions using the number of preceding site visits. These results indicate that analysts benefit less from conducting site visits with preceding visits, or conducting site visits with other investors. Our H6 and H7 are supported.

[Table 7 about here]

5 Additional Analyses

5.1 Site visits and analysts' geographic distance to firms

Malloy(2005) finds that local analysts outperform their distant counterparts in terms of forecast accuracy. This home bias effect is robust in other settings.[15] However, the mechanism through which geographic proximity creates information advantage remains unexplored.[16] The literature focues more on "whether location matters," and less on "why location matters." In this section we examine one potential source of information advantage: analysts' corporate site visits. Bae et al.(2008) propose that a plausible explanation for the local information advantage is that analysts gain access to soft information, on-site observation of the operation activities, and direct interaction with executives. This explanation has largely been taken as a given and no study yet provides a direct test on how local analysts gain local information advantage.

To examine whether analysts' site visits explain the relationship between geographic proximity and information advantage, we compare coefficients on geographic proximity with and without controlling for site visits for analyst forecast accuracy. If the significant positive relationship between geographic proximity and forecast accuracy becomes insignificant when the site visit indicator is controlled for, then the effect of geographic proximity on information advantage is largely driven by the site visit effect.

Table 8 presents the results. We use the geographic distance as independent variables in column (1), and we add the site visit indicator to the regression model in column (2). We find that after adding the site visit indicator, the coefficient of geographic distance changes from significantly negative in Column (1) to insignificant in Column (2). This suggests that site visits

[15] Geographic proximity or "home bias" may influence a variety of economic behaviors. These include holding a higher proportion of local stocks in investment portfolios (Grinblatt and Keloharju 2001), higher returns of fund investors on their investments in local firms (Coval and Moskowitz 2001), more accurate forecasts by analysts about firms in closer proximity to their own brokerage firms (Malloy 2005), and higher acquirer returns for acquisitions within closer geographic proximity (Uysal et al. 2008).

[16] Malloy(2005) conjectures that this is because local analysts have information advantage over other analysts but he did not formally test this hypothesis. He only presents indirect evidence that geography effects are strongest for firms located in small cities and remote areas, where the access to private information is likely to be strongest and competition for that information is weakest.

contribute to home bias: The geographic distance is not really an information barrier as long as analysts are willing to pay site visits to companies.

If conducting site visits help analysts gain information advantage, we examine whether analysts with geographic proximity benefit more from site visits. We add the geographic distance and its interaction with the site visit indicator to the following equation:

$$\begin{aligned}\Delta AFE_{k,j,t} = \alpha + \beta_1 Distance_{k,j,t} + \beta_2 Visit_{k,j,t} + \beta_3 Visit_{k,j,t} * Distance_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} \\ + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} \\ + Industry_{j,t} + \varepsilon_{k,j,t}\end{aligned}$$

As reported in Table 8, we find a negative coefficient on the interaction item. This result shows that local analysts benefit more from site visits to local firms. Our results complement prior studies of analysts' local advantage by showing a mechanism (i.e., by visiting local firms) through which local analysts have an information advantage over non-local analysts.

[Table 8 about here]

5.2 The market reaction to earnings forecasts

In this section we investigate whether the market reaction of the forecasts issued by a visiting analyst is stronger than that of the forecasts issued by a non-visiting analyst. For this purpose, we estimate the following OLS model:

$$\begin{aligned}ABSAR_{j,t} = \alpha + \beta_1 Visit\_ONE_{j,t} + \gamma_1 Firmexp_{j,t} + \gamma_2 Genexp_{j,t} + \gamma_3 Brokersize_{j,t} \\ + \gamma_4 ANA_{j,t} + \gamma_5 BM_{j,t} + \gamma_6 Size_{j,t} + \gamma_7 TURNOVER_{j,t} + \gamma_8 Ret\_Volatility_{j,t} \\ + \gamma_9 Momentum21_{j,t} + \gamma_{10} Momentum252_{j,t} + + Industry_{j,t} + \varepsilon_{j,t}\end{aligned}$$

We use stock price changes during the [-1, +1] event window of analysts' forecasts to capture the market reaction to analysts' forecasts. Specifically, we measure the market reaction to analyst forecasts using the absolute abnormal returns (*ABSAR*), calculated as the absolute value of the cumulated market adjusted abnormal returns in the three-day [-1, +1] window. We

use an estimation period of 250 days in the forecast window [-251, -2] and we require at least 150 trading day observations in this estimation period.

Considering that multiple brokers may issue forecasts for the same firm on the same day, the market reaction for a specific event window can result from a combination of both forecasts issued by visiting analysts and non-visiting analysts. We use two ways to code the indicator of site visits. The indicator variable of site visits (*Visit_ONE*) is coded as 1 if any analyst that issues forecasts on the event day is associated with a broker that has visited firm j in the prior year, or 0 otherwise. The indicator variable of site visits (*Visit_MAJ*) is coded as 1 if more than half of the analysts who issue forecasts on the event day are associated with brokers that have visited firm j in the prior year, or 0 otherwise.

To investigate the effect of site visits on the market reaction to analysts' forecasts, we run a regression of abnormal absolute returns on *Visit_ONE* or *Visit_MAJ*, after controlling for all forecast-level and analyst-level control variables, as in our main tests, and firm characteristics such as firm size, intangibility, leverage, book to market ratio, return volatility, and stock momentum. To rule out the possibility that our results are driven by those observations that coincide with other information disclosure, we exclude event days that fall within the [-1, +1] time window of annual reports, semi-annual reports, and quarterly reports.

Table 9 reports regression results. We find that the market reacts more strongly to forecasts when at least one analyst on the forecast issuance day is associated with a visiting broker (t=2.36) or when more than half of the analysts on a forecast day are associated with visiting brokers (t=2.06).

[Table 9 about here]

6 Conclusion

This study examines how analysts' active information acquisition efforts affect their forecast performance. Using the mandatory disclosure of analysts' corporate site visits in China, we find that the earnings forecasts issued by analysts who conduct site visits to the target firm, are more accurate than those issued by non-visiting analysts, as evidenced by the greater improvement of forecast accuracy in the post-site visit period. The relative accuracy improvement is more pronounced for firms with better corporate governance, for firms with more volatile earnings, for firms with greater market share, and for analysts with longer firm-specific experience. Further evidence shows that the usefulness of site visits can be preempted by preceding visits, and can be diluted by the existence of other visitors in the same site visit. These results suggest that corporate site visits play an important role in analysts' information advantage.

The additional analyses enforce the importance of site visits by showing that geographic proximity increases the usefulness of analysts' site visits and that the market reaction to visiting analysts' forecasts is larger than that to the forecasts made by non-visiting analysts.

Overall, our study shows evidence that analysts forecast accuracy is promoted by these analysts' actively acquisition activities which are usually not observable and hence cannot be identified by prior studies. This paper also provide complementary evidence for the select access literature, especially studies on investors' site visits, by showing the mechanism through which the site visits convey information into the capital market – analysts incorporate the information from site visits into their earnings forecasts by making more accurate earnings forecasts.

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APPENDIX A

A site visit example: Extract of the 2011 annual report of Shenzhen MTC Co., Ltd.

Details of site visits are as follows during the reporting period:

Time	Place	Visitor	Content of discussion and materials provided
Sep. 13 2011	Headquarters	CITIC Securities	The general situation of the export business of high definition digital receivers and LCD TVs; the general situation of the overseas market; the present development status of LED and LED packaging; the future development strategy of the company.
Dec. 1, 2011	Headquarters	Zhongshan Securities, Hangzhou Yinhe Management	Production and operation in the company's first three quarters; the business model and the supply chain management of the company; the general trends in the industry.
Dec. 8, 2011	Fuyong Factory, Shajing Factory, Zhaochi Industrial Park	Shanghai Securities News, Securities Times, Securities Daily, China Securities Journal, Lion Fund Management, Goldstate Securities, GF Securities, Shenzhen Wansheng Investment Management	Brief introduction to the company, its products and product lines, business model, core competitive advantage, sales in the first three quarters, LED business development status, and investment philosophy; the development plan and the size of Zhao Chi Industrial Park.
Dec. 28, 2011	Fuyong Factory, Shajing Factory, Zhaochi Industrial Park	China Securities Journal, Guosen Securities, China Merchants Securities, Huaxi Securities, Hwabao Securities, Great Wall Securities	Brief introduction to the company, its products and product lines, business model, core competitive advantage, sales in the first three quarters, LED business development status, and investment philosophy; the development plan and the size of Zhao Chi Industrial Park.

In the reporting period, the company received eight site visits from investors and analysts. During these site visits, the company strictly followed the regulations in the Guidelines of Fair Information Disclosure for Companies Listed on the Small and Medium-Sized Enterprise Board of the Shenzhen Stock Exchange, the Guidelines of the Shenzhen Stock Exchange for Standardized Operation of Companies Listed on the Small and Medium-Sized Enterprise Board, and the internal guidelines of information disclosure and investor relationship management of the company. The company fairly treats each investor during the site visit process. Investors have to register with the company before their site visits; investors are strongly suggested to avoid those dates that coincide with other significant information disclosure time windows when scheduling site visits. Before site visits, all visitors are required to sign an agreement to follow the company's site visit policy, and during the site visits, visitors are accompanied by more than two staff members of the company, who shall record the conversation and report it to the Shenzhen Stock Exchange.

APPENDIX B
Variable definitions

Panel A: Variable definitions for the forecast accuracy analysis

Dependent Variables

$\Delta AFE_{k,j,t} = -(Post\_Visit\_AFE_{k,j,t} - Pre\_Visit\_AFE_{k,j,t})$

$\Delta AFE\_Mean_{k,j,t}$	=	The change of absolute forecast error of analyst group k for firm j from 6 months before site visit event t to 1 month after site visit event t. We added a negative sign to the difference so that a positive value implies the improvement in forecast accuracy. k marks two types of analyst groups for each site visit event t, the visiting-group or the non-visiting group. More specifically, based on whether an analyst visits firm j on a site visit event day t, we identify a group of visiting analysts and a group of non-visiting analysts for each site visit event t. for each analyst group, we first calculate the mean or median of every analyst's most recent annual EPS forecasts prior to site visit as the consensus forecast of this group, and then calculate the pre-site visit absolute forecast errors for this group (i.e., *Pre_Visit_AFE*). The forecast error is measured as the difference between consensus forecast and actual EPS, scaled by stock price at the beginning of the firm-year. Similarly, we identify the most recent forecasts made by the same group of analysts prior to the one month after site visits, calculate their forecast consensus and develop the absolute forecast error for the same group in the post-site visit period (i.e., *Post_Visit_AFE*). Then, we use the difference in forecast accuracy between post-site visit and pre-site visit periods (ΔAFE).
$\Delta AFE\_Median_{k,j,t}$	=	Similar as above, only that we calculate the *pre_visit_AFE* or *post_visit_AFE* on the basis of forecast consensus proxied by the median value of forecasts made by this group of analysts.

Key Variable

$Visit_{k,j,t}$	=	An indicator variable of whether individual analyst forecasts are issued by an analyst associated with a visiting broker. Coded as 1 if analyst i is associated with a visiting broker. Visiting brokers are coded based on specific site visit events. For each site visit event t, we identify the brokers who visited on the site visit event day t and t-1 as visiting analysts and all other analysts as non-visiting analysts.

Variables for Cross-sectional analyses

Dual	=	An indicator variable that equals to 1 if the Chairman and the CEO is the same individual for firm j in current year, and 0 otherwise.
Indep	=	The ratio of the number of independent directors to all directors for firm j in current year.
NI_std	=	The standard deviation of net income for firm j, which equals to the standard deviation of net income during past five years (including current year)
MSHARE	=	Market share of firm j in current year, which equals to revenue of the

		firm j devided by the total revenue of all firms in same 3-digit CSRC industry.
Pure	=	An indicator of pure visits, which equals to 1 if all visitors are visiting analysts and there is no any other non-analyst visitor (such as fund or bank etc), and 0 otherwise.
Preceding_visits	=	The logged number of site visits of firm j within one month before the current site visit t.
Distance	=	The median of the geographic distance between all brokers in group k and firm j in current year.

Control Variables

$\Delta horizon_{k,j,t}$	=	The change of average forecast horizon of analyst group k (visiting group or non-visiting group) from pre-visit to post-visit. Forecast horizon is defined as the number of calendar days between the forecast issue date and the corresponding earnings announcement dates.
Firmexp	=	Analyst firm-specific experience, designed as the log transformation of average firm-specific experience of all analysts in analyst group k for firm j. Firm specific experience is the time interval in years between his first forecast for a particular firm j and his current forecast for firm j.
Brokersize	=	Broker size, defined as the average number of analysts working for the brokers in group k.
NumANA	=	The log transformation of the number of analysts in each group k.
MV	=	The log transformation of the market value of equity of firm j at the end day of last fiscal year.

Panel B: Variable definitions for the analysis of forthcoming earnings news (Firm-year-event day level)

Dependent Variables		
ABSAR	=	The absolute 3-day model-adjusted cumulated abnormal returns around a forecast issued by analyst i of firm j's fiscal year T earnings. The market model is estimated based on day -251 to day -2 and at least 150 observations are required for estimating the market model within this period.
Independent Variables		
Visit_ONE	=	An indicator variable for analyst site visits on the forecast event day. It is coded as 1 if at least *one* analyst who issue forecast on the event day is associated with a visiting broker. To identify a visiting broker we perform same procedure as when coding the variable *Visit.*
Visit_MAJ	=	An indicator variable for analyst site visits on the forecast event day. It is coded as 1 if more than half of the analysts who issue forecasts on the event day are associated with visiting brokers. To identify a visiting broker we perform same procedure as when coding the variable *Visit.*
Control Variables – Broker Level		
Δhorizon	=	Number of calendar days between the forecast issue date and the corresponding earnings announcement dates. (Demeaned)
Brokersize	=	Broker size, defined as the number of analysts working for the brokerage firm that analyst i is associated with. (Demeaned)
Firmexp	=	Analyst firm-specific experience, designed as the log transformation of the time interval in years between analyst i's first forecast for a particular firm j and his forecast at time t for firm j. (Demeaned)
Genexp	=	Analyst general experience, defined as the log transformation of the time interval in years between analyst i's first forecast in the CSMAR database and the current forecast at time t. (Demeaned)
Control Variables – Firm Level		
ANA	=	Natural logarithm of 1 plus the total number of analysts that cover firm j in year T.
BM	=	The book-to-market ratio of firm j at the fiscal year end prior to the forecast event date.
Size	=	The natural logarithm of the market value of the firm j at the fiscal year end prior to the forecast event date.
TURNOVER	=	The average monthly share turnover of firm j, computed as volume divided by shares outstanding, over the 63 days prior to the forecast event date.
Ret_Volatility	=	Standard deviation of daily returns of firm j over the 63 days prior to the forecast event date.
Momentum21	=	Stock return of firm j over the 21 trading days prior to the forecast event date.
Momentum252	=	Stock return of firm j over the prior 252 trading days prior to the recommendation, excluding the 21 trading days prior to the recommendation.

TABLE 1
Sample selection

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

	# of total site visits	2009	2010	2011	2012
Site visits involved with brokerage firms.	18,078	2,233	3,860	4,682	7,303
Requiring at least one analyst forecast for annual EPS of the coming year in the period of 6 months prior to site visit dates.	16,849	1,955	3,548	4,430	6,995
Combining site visits with adjacent event dates as one event.	15,787	1,832	3,320	4,131	6,504
Deleting the firms in the financial industries and those firms without data for the calculation of forecast accuracy.	15,476	1,754	3,222	4,057	6,443
Requiring earnings forecasts made by visiting analysts in the period of six months prior to site visits to one month after site visits	7,462	681	1,564	1,909	3,308
Requiring at least one earnings forecast made by visiting analysts in the pre-site visit period of six months prior to site visits	5,068	387	944	1,293	2,444
Requiring earnings forecast accuracy for non-visiting analyst group in both the pre-site visit and post-site visit periods	4,947	367	915	1,263	2,402

TABLE 2
Descriptive statistics for the subsamples of visiting analysts and non-visiting analysts

This table shows summary statistics of the main variables used in the analysis. The sample firms are 9,894 group forecasts, including 4,947 forecasts issued by visiting groups and non-visiting groups, respectively. We add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of *ΔAFE* implies the improvement in forecast accuracy. Please see Appendix B for the variable definitions. ***, **, * indicate the coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Variables	*Visit*=0(A)		*Visit*=1(B)		B-A	
	Mean	Median	Mean	Median	Mean (t-test)	Median (Wilcoxon test)
ΔAFE_Mean	0.0252	0.0000	0.0574	0.0000	8.38***	4.08***
ΔAFE_Median	0.0229	0.0000	0.0590	0.0000	8.87***	0.49
Δhorizon_Mean	98.0362	94.8333	85.6684	76.0000	-15.1***	-20.59***
Δhorizon_Median	93.2326	87.0000	85.3490	74.0000	-8.57***	-11.7***
Firmexp_Mean	2.3234	2.0000	2.5672	2.0000	7.56***	2.54**
Firmexp_Median	2.2092	2.0000	2.5661	2.0000	10.7***	5.78***
Brokersize_Mean	30.6500	30.5000	35.4187	36.0000	25.09***	25.67***
Brokersize_Median	30.4690	30.0000	35.4231	36.0000	25.08***	25.61***
No. of obs.	4,947		4,947			

TABLE 3
The change of forecast accuracy for visiting and non-visiting analysts around site visits.

This table presents the OLS regressions result of forecast accuracy change on the site visit indicator, analyst characteristics, and control variables.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (ΔAFE). In the definition of ΔAFE, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of ΔAFE implies the improvement in forecast accuracy. The full sample consists of 9,894 forecasts in the period of 2009-2012. The t-values in parentheses are based on standard errors adjusted for firm and year 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 variable definitions.

Variables	Column (1) *ΔAFE_Mean*	Column (2) *ΔAFE_Median*
Visit	0.0391***	0.0408***
	(16.01)	(14.55)
Δhorizon_Mean	0.0169***	
	(3.01)	
Firmexp_Mean	0.0148***	
	(5.20)	
Brokersize_Mean	-0.0276***	
	(-2.77)	
Δhorizon_Median		0.0192***
		(2.94)
Firmexp_Median		0.0134***
		(4.83)
Brokersize_Median		-0.0254***
		(-3.48)
NumANA	0.0156***	0.0165***
	(3.54)	(4.02)
MV	-0.0057***	-0.0060***
	(-2.92)	(-3.84)
Industry Fixed Effects	Yes	Yes
Observations	9,894	9,894
Adj. R^2	0.013	0.014

TABLE 4
The effect of firms' corporate governance on the usefulness of analysts' site visits

This table presents the OLS regression results of the forecast accuracy change on the site visit indicator, conditional on duality and board independence.

Column(1)-(2) report the regression results of forecasts accuracy change on the visit indicator, duality indicator, and their interaction term based on the following model. The duality indicator variable (*Dual*) equals to 1 if the manager and chair director are same, 0 otherwise.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Dual_{j,t} + \beta_3 Visit_{k,j,t} * Dual_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

Column(3)-(4) report the regression results of forecasts accuracy change on the visit indicator, the independence of director, and their interaction term based on the following model. The board independence variable (*Indep*) equals to the percentage of independent directors on board.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Indep_{j,t} + \beta_3 Visit_{k,j,t} * Indep_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (ΔAFE). In the definition of ΔAFE, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of ΔAFE implies the improvement in forecast accuracy. The full sample consists of 9,894 forecasts in the 2009-2012 periods. The t-values in parentheses are based on standard errors adjusted for firm and year 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 variable definitions.

TABLE 4 (Cont'd)

Variables	CEO-Chairman Duality		Board Independence	
	Column (1)	Column (2)	Column (3)	Column (4)
	ΔAFE_Mean	*ΔAFE_Median*	*ΔAFE_Mean*	*ΔAFE_Median*
Visit	0.0428***	0.0450***	0.0159**	0.0235**
	(12.99)	(10.38)	(2.49)	(2.33)
Dual	0.0016	0.0031		
	(0.94)	(1.51)		
*Visit*Dual*	-0.0126***	-0.0141**		
	(-3.19)	(-2.30)		
Indep			-0.0256	-0.0158
			(-0.85)	(-0.84)
*Visit*Indep*			0.0621***	0.0462**
			(4.90)	(2.10)
Δhorizon_Mean	0.0175***		0.0167***	
	(3.28)		(2.94)	
Firmexp_Mean	0.0147***		0.0151***	
	(5.88)		(5.29)	
Brokersize_Mean	-0.0269**		-0.0267**	
	(-2.57)		(-2.51)	
Δhorizon_Median		0.0196***		0.0191***
		(3.12)		(2.89)
Firmexp_Median		0.0132***		0.0136***
		(5.26)		(4.85)
Brokersize_Median		-0.0247***		-0.0244***
		(-3.17)		(-3.04)
NumANA	0.0155***	0.0165***	0.0160***	0.0168***
	(3.48)	(3.94)	(3.54)	(4.06)
MV	-0.0059***	-0.0062***	-0.0056***	-0.0059***
	(-2.94)	(-3.75)	(-2.72)	(-3.59)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,840	9,840	9,852	9,852
Adj. R^2	0.013	0.014	0.013	0.013

TABLE 5
The effect of analysts' firm-specific experience on the usefulness of analysts' site visits

This table reports the analysis of forecast accuracy changes of visiting analysts and non-visiting analysts with analysts' characteristic (*Firmexp*), based on the following model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Firmexp_{k,j,t} + \beta_3 Visit_{k,j,t} * Firmexp_{k,j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Brokersize_{k,j,t} + \gamma_3 NumANA_{k,j,t} + \gamma_4 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (ΔAFE). In the definition of ΔAFE, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of ΔAFE implies the improvement in forecast accuracy. The full sample consists of 9,894 forecasts in the period of 2009-2012. The t-values in parentheses are based on standard errors adjusted for firm and year 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 variable definitions.

Variables	Column (1) *ΔAFE_Mean*	Column (2) *ΔAFE_Median*
Visit	0.0303***	0.0308***
	(5.24)	(6.39)
Firmexp	0.0142**	0.0104***
	(2.52)	(3.64)
Visit Firmexp*	0.0127*	0.0172***
	(1.83)	(3.57)
Δhorizon_Mean	0.0170***	
	(2.98)	
Brokersize_Mean	-0.0266***	
	(-2.76)	
Δhorizon_Median		0.0191***
		(2.88)
Brokersize_Median		-0.0245***
		(-3.46)
NumANA	0.0155***	0.0163***
	(2.92)	(3.52)
MV	-0.0051***	-0.0054***
	(-2.61)	(-4.22)
Industry Fixed Effects	0.0072	0.0148
Observations	9,894	9,894
Adj. R^2	0.014	0.014

TABLE 6

The effect of firms' earnings volatility and market shares on the usefulness of analysts' site visits

This table presents the OLS regression results of the forecast accuracy change on the site visit indicator, conditional on earnings volatility and market share.

Column(1)-(2) report the regression results of forecasts accuracy change on the visit indicator, earnings volatility, and their interaction term based on the following model. The earnings volatility (*NI_std*) is the standard deviation of net income during past five years (including current year).

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 NI\_std_{j,t} + \beta_3 Visit_{k,j,t} * NI\_std_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

Column(3)-(4) report the regression results of forecasts accuracy change on the visit indicator, the market share, and their interaction term based on the following model. The market share (MSHARE) equal to Sales of firm j divided by the sum of sales of all listed firms that belong to the same first 3-digit CSRC industrial code in year t.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 MSHARE_{j,t} + \beta_3 Visit_{k,j,t} * MSHARE_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (Δ*AFE*). In the definition of Δ*AFE*, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of *ΔAFE* implies the improvement in forecast accuracy. The full sample consists of 9,894 forecasts in the 2009-2012 periods. The t-values in parentheses are based on standard errors adjusted for firm and year 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 variable definitions.

Variables	Volatility of net income		Market share	
	Column (1)	Column (2)	Column (3)	Column (4)
	ΔAFE_Mean	*ΔAFE_Median*	*ΔAFE_Mean*	*ΔAFE_Median*
Visit	0.0288***	0.0266***	0.0368***	0.0382***
	(15.49)	(11.91)	(15.42)	(12.36)
NI_std	0.0721*	0.0266		
	(1.85)	(0.55)		
*Visit*NI_std*	0.1947***	0.2568***		
	(4.68)	(4.63)		
MSHARE			0.0312	0.0347
			(1.50)	(1.09)
*Visit*MSHARE*			0.0471**	0.0512***
			(2.46)	(2.95)
Δhorizon_Mean	0.0178***		0.0166***	
	(2.98)		(2.93)	

Firmexp_Mean	0.0173***		0.0144***	
	(5.59)		(4.14)	
Brokersize_Mean	-0.0285***		-0.0270**	
	(-2.76)		(-2.56)	
Δhorizon_Median		0.0198***		0.0189***
		(2.89)		(2.84)
Firmexp_Median		0.0151***		0.0129***
		(4.89)		(3.89)
Brokersize_Median		-0.0261***		-0.0248***
		(-3.45)		(-3.15)
NumANA	0.0145***	0.0158***	0.0149***	0.0158***
	(2.75)	(3.27)	(4.43)	(4.87)
MV	-0.0066**	-0.0069***	-0.0068***	-0.0072
	(-2.20)	(-2.63)	(-5.47)	(.)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	9,734	9,734	9,842	9,842
Adj. R^2	0.016	0.016	0.013	0.013

TABLE 7

The effect of preceding site visits and other visitors on the usefulness of analysts' site visits

This table presents the OLS regression results of the forecast accuracy change on the site visit indicator, conditional on group visits and preceding visits.

Columns (1) and (2) report the regression results of forecasts accuracy change on the visit indicator, pure visits indicator, and their interaction term based on the following model. The pure visits indicator variable (*Pure*), equal to 1 if the broker went to site visit together with other brokers, but not any other visitors, such as fund or bank etc, 0 otherwise.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Pure_{j,t} + \beta_3 Visit_{k,j,t} * Pure_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

Column(3)-(4) report the regression results of forecasts accuracy change on the visit indicator, the preceding visits, and their interaction term based on the following model. The preceding visits variable (*Preceding_visits*), is the logged number of site visits that precede the current one in the time window of the prior 1 month before event date.

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Visit_{k,j,t} + \beta_2 Preceding\_visits_{j,t} + \beta_3 Visit_{k,j,t} * Preceding\_visits_{j,t} + \gamma_1 \Delta Horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (ΔAFE). In the definition of ΔAFE, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of ΔAFE implies the improvement in forecast accuracy. The full sample consists of 9,894 forecasts in the period of 2009-2012. The t-values in parentheses are based on standard errors adjusted for firm and year 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 variable definitions.

Variables	Pure visit		Preceding visit	
	Column (1)	Column (2)	Column (3)	Column (4)
	ΔAFE_Mean	*ΔAFE_Median*	*ΔAFE_Mean*	*ΔAFE_Median*
Visit	0.0333***	0.0329***	0.0428***	0.0425***
	(7.29)	(6.94)	(17.11)	(16.11)
Pure	0.0007	-0.0031		
	(0.18)	(-0.79)		
*Visit*Pure*	0.0188**	0.0256***		
	(2.48)	(3.17)		
Preceding_visits			-0.0008	-0.0014
			(-0.48)	(-0.85)
*Visit*Preceding_visits*			-0.0022***	-0.0010***
			(-2.82)	(-5.28)
Δhorizon_Mean	0.0177***		0.0172***	
	(3.75)		(2.95)	

Firmexp_Mean	0.0119***		0.0147***	
	(2.60)		(5.27)	
Brokersize_Mean	-0.0269***		-0.0273***	
	(-3.21)		(-2.80)	
Δhorizon_Median		0.0200***		0.0195***
		(4.70)		(2.86)
Firmexp_Median		0.0109**		0.0132***
		(2.46)		(4.81)
Brokersize_Median		-0.0241***		-0.0251***
		(-3.05)		(-3.56)
NumANA	0.0102	0.0116*	0.0164***	0.0172***
	(1.54)	(1.77)	(4.11)	(4.68)
MV	-0.0006	-0.0016	-0.0052**	-0.0055**
	(-0.16)	(-0.40)	(-2.11)	(-2.50)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Constant	-0.0224	-0.0206	0.0927***	0.0742***
	(-0.26)	(-0.23)	(6.90)	(2.64)
Observations	9,894	9,894	9,894	9,894
Adj. R^2	0.016	0.015	0.013	0.014

TABLE 8
The effect of geographic proximity on the usefulness of analysts' site visits

This table presents the OLS regression results of the forecast accuracy change on the site visit indicator, and distance in following model:

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Distance_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Distance_{k,j,t} + \beta_2 Visit_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

$$\Delta AFE_{k,j,t} = \alpha + \beta_1 Distance_{k,j,t} + \beta_2 Visit_{k,j,t} + \beta_3 Visit_{k,j,t} * Distance_{k,j,t} + \gamma_1 \Delta horizon_{k,j,t} + \gamma_2 Firmexp_{k,j,t} + \gamma_3 Brokersize_{k,j,t} + \gamma_4 NumANA_{k,j,t} + \gamma_5 MV_{j,t} + Industry_{j,t} + \varepsilon_{k,j,t}$$

The dependent variable is the change of forecast accuracy for every group (ΔAFE). In the definition of ΔAFE, we add a negative sign to the difference in absolute forecast errors between pre-site visit and post-site visit periods, and a positive value of ΔAFE implies the improvement in forecast accuracy. *Distance* is indicator variable, equal to 1 if the average geographic distance between the headquarters of firm j and all analysts who follow this firm is greater than the median, 0 otherwise. Control variables are shown in Panel A of Appendix B. Column (1) reports the regression results of forecast accuracy change on the geographic distance based on the first model above, and Column (2) reports the regression results of forecast accuracy change on the site visit indicator and the geographic distance based on the second model above, Column (3) reports the regression results of forecast accuracy change on the site visit indicator ,the geographic distance, and their interaction term. The t-values in parentheses are based on standard errors adjusted for firm and year clustering. ***, **, * indicate the coefficients that are significant at the 0.01, 0.05, and 0.10 levels, respectively, based on two-tailed statistical tests.

Variables	*ΔAFE_Mean*			*ΔAFE_Median*		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-0.0045	-0.0006	0.0039*	-0.0068***	-0.0025	0.0003
	(-1.32)	(-0.17)	(1.72)	(-3.01)	(-1.14)	(0.11)
Visit		0.0389***	0.0433***		0.0404***	0.0433***
		(14.70)	(16.45)		(14.57)	(11.46)
*Visit*Distance*			-0.0089**			-0.0058
			(-2.23)			(-0.83)
Δhorizon_Mean	0.0081*	0.0171***	0.0171***			
	(1.74)	(2.97)	(2.98)			
Firmexp_Mean	0.0138***	0.0148***	0.0148***			
	(4.20)	(5.22)	(5.19)			
Brokersize_Mean	-0.0186**	-0.0272***	-0.0268***			
	(-2.00)	(-2.73)	(-2.66)			
Δhorizon_Median				0.0146**	0.0193***	0.0194***
				(2.24)	(2.91)	(2.92)
Firmexp_Median				0.0153***	0.0134***	0.0134***

				(4.40)	(4.86)	(4.86)
Brokersize_Median				-0.0159**	-0.0248***	-0.0246***
				(-2.42)	(-3.45)	(-3.34)
NumANA	0.0154***	0.0158***	0.0157***	0.0152***	0.0167***	0.0166***
	(3.22)	(3.64)	(3.62)	(3.59)	(4.12)	(4.10)
MV	-0.0051***	-0.0057***	-0.0057***	-0.0059***	-0.0059***	-0.0059***
	(-2.86)	(-3.24)	(-3.21)	(-3.72)	(-4.11)	(-4.09)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,886	9,886	9,886	9,886	9,886	9,886
Adj. R^2	0.004	0.013	0.013	0.004	0.013	0.013

TABLE 9
Market reaction to earnings forecasts issued by visiting analysts

This table reports the analysis of how market reacts to forecasts issued by analysts associated with visiting brokers based on the following model:

$$ABSAR_{j,t} = \alpha + \beta_1 Visit\_ONE_{j,t} + \gamma_1 Firmexp_{j,t} + \gamma_2 Genexp_{j,t} + \gamma_3 Brokersize_{j,t} + \gamma_4 ANA_{j,t} + \gamma_5 BM_{j,t} + \gamma_6 Size_{j,t} + \gamma_7 TURNOVER_{j,t} + \gamma_8 Ret\_Volatility_{j,t} + \gamma_9 Momentum21_{j,t} + \gamma_{10} Momentum252_{j,t} + +Industry_{j,t} + \varepsilon_{j,t}$$

$$ABSAR_{j,t} = \alpha + \beta_1 Visit\_MAJ_{j,t} + \gamma_1 Firmexp_{j,t} + \gamma_2 Genexp_{j,t} + \gamma_3 Brokersize_{j,t} + \gamma_4 ANA_{j,t} + \gamma_5 BM_{j,t} + \gamma_6 Size_{j,t} + \gamma_7 TURNOVER_{j,t} + \gamma_8 Ret\_Volatility_{j,t} + \gamma_9 Momentum21_{j,t} + \gamma_{10} Momentum252_{j,t} + +Industry_{j,t} + \varepsilon_{j,t}$$

The variable definitions are shown in Panel B of Appendix B. The full sample consists of 12,477 unique forecast date in the 2009-2011 periods. Column (1) and (2) report the regression results when dependent variable (*ABSAR*) is the absolute value of cumulated abnormal returns in the 3-day event window centered on analyst forecast based on market model. While Column (3) and (4) report the regression results based on market adjusted model (e.g. abnormal return equal to the difference between individual stock price and value-weighted market returns). The t-values in parentheses 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.

Variables	Column (1) *ABSAR*	Column (2) *ABSAR*	Column (3) *ABSARAJ*	Column (4) *ABSARAJ*
Visit_ONE	0.0017**		0.0019***	
	(2.36)		(2.65)	
Visit_MAJ		0.0014**		0.0016**
		(2.06)		(2.12)
Firmexp	0.0010***	0.0010***	0.0011***	0.0011***
	(3.51)	(4.01)	(4.05)	(3.73)
Genexp	0.0008***	0.0008***	0.0007***	0.0007***
	(4.84)	(4.90)	(4.59)	(4.62)
Brokersize	-0.0004	-0.0003	-0.0005	-0.0003
	(-0.54)	(-0.37)	(-0.63)	(-0.41)
ANA	-0.0018**	-0.0022***	-0.0015**	-0.0021***
	(-2.45)	(-3.92)	(-2.11)	(-3.05)
BM	-0.0075**	-0.0063***	-0.0082***	-0.0067**
	(-2.51)	(-2.81)	(-2.81)	(-2.40)
Size	-0.0010**	-0.0004	-0.0010**	-0.0004
	(-1.98)	(-1.03)	(-2.17)	(-0.80)
TURNOVER	0.0008	0.0008	0.0009	0.0009
	(1.13)	(1.59)	(1.23)	(1.31)
Ret_Volatility	0.0117***	0.0129***	0.0101***	0.0113***
	(6.24)	(7.91)	(5.27)	(5.95)
Momentum21	0.0176***	0.0179***	0.0193***	0.0196***
	(6.13)	(7.95)	(6.59)	(6.63)
Momentum252	0.0016**	0.0018***	0.0018**	0.0020***

	(2.02)	(3.21)	(2.43)	(2.65)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Constant	0.1011***	0.0918***	0.0965***	0.0858***
	(9.11)	(10.08)	(9.26)	(8.25)
Observations	12,477	12,477	12,477	12,477
Adj. R^2	0.031	0.027	0.030	0.026