Investor Corporate Visits and Predictable Returns

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Abstract

Using a unique dataset of firms listed on China's Shenzhen Stock Exchange, we show that investors' corporate site visits convey information about future stock returns. Firms with abnormally frequent investor visits predictably outperform firms with abnormally infrequent investor visits by approximately 70-to-100 basis points per month. This return predictability concentrates in neglected firms with low trading volumes and when investors incur higher travel costs. Abnormally frequent investor visits accompany increased holdings among visiting institutions and predict improvements in firms' fundamental performance, consistent with institutions using visits to gain an information advantage regarding underpriced firms.

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"The significance of conducting site visits and in-depth research by fund companies is to consistently deliver stable and substantial returns to clients through professional expertise."

—— Lei Jing, CEO of Harvest Fund Management Co., Ltd., China.

I. Introduction

In 2022 alone, China's A-share firms attracted over 20,000 investor site visits, encompassing mutual and hedge funds, marking a tenfold increase from the 2012 figure of around 2,000. Our interviews with fund managers from China's top mutual fund firms revealed that they dedicate a staggering 40-50% of their working hours to these site visits. Thus, analyzing variation in site-visits provides crucial insights into the actual investment process used by institutional investors and the signal content provided by their choices.

Despite the rise in online communication and information gathering, site visits remain crucial for investors and financial analysts (Jackson (2009) and Institutional Investor's All-Europe Research Team Survey (2012)). These visits offer insights into the company's operations, culture, and management, aiding investor decision-making. Moreover, they offer investors the opportunity to ask questions and interact with the management team, fostering trust and relationships. As investors are physically present during in-person visits, they can observe management teams better and garner sharper visual signals and social context cues (e.g., facial expression, vocal tone, body language, body posture, and gestures) than in virtual meetings. Moreover, they reveal operational facets, such as supply chains and production processes, that are not readily apparent from financial statements.

This study investigates the links between investor in-person visits, price discovery, and future stock returns. Our central hypothesis is that the frequency of investors' corporate site visits indicates the extent of underpricing. This is because institutional investors tend to disproportionately allocate their portfolios toward long positions relative to short positions. Thus, we expect investors to be more likely to visit firms to seek positive signals regarding firm value (e.g., successful prototypes or processes) than negative signals.

We separate site visits into an expected component, based on observable firm characteristics, and an abnormal component unrelated to firm size, liquidity, and past performance, which we show strongly predicts future returns. In doing so, our findings contribute to the literature on firm-level expected returns and offer significant insights into belief formation, price discovery, and sophisticated investor vetting processes. Specifically, our results indicate that institutions invest significant resources in site visits to underpriced firms, and that the frequency of these visits positively predicts future returns.

We focus specifically on site visits because they are arguably the most costly form of in-person visits for investors, and thus more likely informative of the costs investors are willing to bear to learn about a firm.[1] They are the most costly in that they require investors to travel to firms' locations of commerce or operations, rather than hosting firms' representatives, i.e., roadshows, or meeting several firms simultaneously via conferences. These visits require allocating limited resources toward a selected subset of the investable universe of firms, which poses both direct costs to investors, such as employee salaries and travel expenses, and indirect costs such as potential price slippage and forgone investment opportunities. As compensation for

[1]The 2012 Institutional Investor's All-Europe Research Team Survey shows that institutional investors rank corporate site visits to be more important than one-on-one conferences with management and analysts' research reports in terms of acquiring information about firms.

bearing these costs, we expect that investors' decisions to visit firms are indicative of their potential payoffs in terms of future equity returns.

Our main tests rely on data for firms listed on the Shenzhen Stock Exchange (SZSE) in China, as SZSE-firms are required to provide detailed and timely disclosures of visits with institutional investors. The other major stock exchange in China, the Shanghai Stock Exchange (SHSE), does not have such mandatory disclosure requirement (we discuss the institutional, especially the disclosure, differences between these two major exchanges in China in the Internet Appendix Section 5). Moreover, no such rule exists internationally, which helps explain why prior U.S. studies are limited to small sample data from specific firms (e.g., Soltes (2014)).

In speaking with fund managers, a common takeaway is that funds pursue site visits to assess the quality of firms' management and tour production facilities. To better understand the institutional setting, we conducted in-depth interviews of three institutional fund managers as well as three investor relations (IR) managers for firms in our sample. The key takeaways are: (1) fund managers typically spend 40-50% total working hours visiting listed firms, indicating that site visits pose significant costs; (2) IR managers report that site visits are almost entirely initiated by institutions, rather than by the firms being visited; and (3) fund managers garner more information and sharper insights from site visits than remote virtual meetings (See Appendix A for more details).

Our data indicates roughly 75% of investor site visits between firms and mutual funds (only mutual funds are required to disclose fund holdings in China A-share market) first occur before the institution initiates a position, indicating such visits are a recurring feature of the institutional vetting process. Our data also shows more than half of all SZSE-listed firms host investor visits in a given year, and hosting firms meet with institutions approximately four times per year on average. There is also considerable cross-sectional variation in these visits, which we seek to exploit in our empirical tests.

We develop a simple characteristic-based model to extract information about future returns from investor site-visit data. Our approach seeks to isolate the component of site visits driven by investors' expectations over firms' future returns, which we call abnormal investor visits (AIV). Specifically, we run cross-sectional regressions of visit frequency on firm characteristics (including firms' size, liquidity, and past performance) each month, and use the regression residual as a signal of AIV. Our central empirical prediction is that AIV signals firm-level underpricing and thus positively predicts future returns.

Our first main tests show abnormal investor visits predict firms' stock returns. On average, firms in the highest quintile of abnormal visits (i.e., high AIV firms) outperform the lowest quintile (i.e., low AIV firms) by 65 basis points per month on a value-weighted basis (t-statistic = 2.92) and 114 basis points on an equal-weighted basis (t-statistic = 5.52). These return patterns are striking in their magnitude and robustness, suggesting abnormal visits are associated with an economically large source of predictable returns.

The predictive power of AIV for returns is distinct from firms' exposure to standard asset pricing factors, standard controls including firms' size, momentum, and profitability, and the return prediction evidence in Lee and So (2017) and Cheng, Du, Wang, and Wang (2019). Strategy returns also do not appear to reverse in subsequent months. In fact, we find that AIV predicts returns over the next six-to-ten months and holds even when controlling for contemporaneous and forward changes in institutional holdings. These findings suggest our findings unlikely stem from transitory institutional price pressure that subsequently reverses.

Abnormal site visits are intuitively more informative of underpricing when institutions are likely incurring greater costs to establish connections and meet with firms. Specifically, the predictive power of AIV for returns is stronger for visits involving institutions that did not own shares of the firm prior to visiting, visits that do not appear as part of a routine schedule of visits, and visits requiring higher travel times. These results are consistent with an equilibrium in which investors are more willing to incur higher costs to vet their beliefs when underpricing is likely more severe. Furthermore, we provide evidence that the return predictability of AIV is more pronounced for neglected firms, i.e., firms with low analyst coverage, low institutional holdings, loss firms, no subsequent revisions, and low abnormal trading volumes.

The second half of our paper focuses on the mechanisms underlying how investors identify underpriced firms. In doing so, we also provide novel evidence on the nature of information that investors accrue that helps justify the cost of visiting firms. For example, our results suggest that a central reason that AIV predicts higher returns is because visited firms are more likely to subsequently report positive earnings announcement news. Specifically, we show that abnormal visits increase ahead of the visited firm reporting positive earnings growth and analyst-based earnings surprises in their next quarterly earnings announcements. Moreover, AIV strategy spread is 360-400$\%$ higher on earnings announcement days than on non-announcement days. These tests suggest institutions seek site visits with ascending firms and use these visits to verify their beliefs ahead of public announcements.

We also provide evidence that our strategy returns likely reflect AIV being a precursor to institutional buying behavior. Using data on institutional holdings, we show AIV tends to rise with increases in institutional holdings of the visited firms. Further, when we dissect institutional holdings, we see that higher AIV explains increased holdings only among institutions having recently visited the firm. In fact, visiting institutions appear to buy shares from non-visiting institutions, consistent with site visits spurring ownership changes by conferring visiting institutions with an information advantage regarding firm value.

Finally, we show institutions that conduct more site visits tend to earn higher alphas, which is consistent with Crane, Crotty, and Umar (2023) showing that hedge funds actively acquiring information outperform non-acquirers. Our findings provide further evidence that funds gain an information advantage through site visits that help justify the costs they incur to meet with firms in person. However, we also show that funds active in visiting firms are disproportionately harmed when they are unable to conduct site visits. Specifically, by updating our sample through the COVID-19 pandemic, we show that travel restrictions brought on by COVID-19 disproportionately harmed funds that rely on such visits in their investment process, which is similar to the Ben-Rephael, Carlin, Da, and Israelsen (2022) findings on traveling analysts experiencing significant reductions in forecast accuracy during the COVID-19 lockdown. These findings help illustrate how disruptions to the economy and travel shape institutional investors' performance and market outcomes by impacting investors' ability to access information through site visits.

Our study contributes to the literature in several ways. First, our paper shows that institutions disproportionately allocate resources to site visits with underpriced firms prior to investing, and rely on face-to-face contact to calibrate potential mispricing. To the best of our knowledge, ours is among the first large sample studies to examine variation in face-to-face measures of investor attention rather than relying on web-searches or financial statement downloads. Prior studies on investor attention (Ben-Rephael, Da, and Israelsen (2017), Drake, Roulstone, and Thornock (2012, 2015), and Da, Engelberg, and Gao (2011)) use Bloomberg, EDGAR, or Google search data to show that institutional investor attention facilitates price adjustment, while retail investor attention predicts higher stock prices in the short term and price reversals in the long run. Because in-person visits likely impose higher costs than internet searches, our evidence of return predictability helps explain why institutions are willing to incur these costs despite the availability of online information. Thus, our findings help paint a more complete picture of the institutional vetting process, and suggest that in-person visits serve a complementary role to web-based information searches in identifying firms worthy of investment.

Second, our paper also contributes to recent studies on corporate site visits by focusing on the selection process used by institutional investors and the signal content that their choices provide. Soltes (2014) and Solomon and Soltes (2015) find that private interaction with management is an important communication channel for analysts and for a select group of investors to make more informed trading decisions. Our study examines cross-sectional variation in these meetings and their implications for future stock returns.

Related findings in Cheng, Du, Wang, and Wang (2016) and Han, Kong, and Liu (2018) highlight improved forecast accuracy among analysts that visit firms in person. Perhaps the most related research to ours is Cheng et al. (2019), which documents significant market reaction (i.e, elevated volatility and trading volume) around site visits, and that the market reaction helps forecast firms' fundamental performance. Our research differs in at least three ways: first, we shift focus away from variation in market outcomes conditional upon a visit occurring (i.e., the sample of firms that were visited), and instead focus on which firms funds choose to visit versus forgo. Second, Cheng et al. (2019) use conventional event-study methods which assume that the market reaction is efficient, whereas we document significant returns to an abnormal-investor-visit based trading strategy due to investors' limited attention. In doing so, we illustrate how other non-visiting investors may benefit from studying variation in site visits. Third, Cheng et al. (2019)

find market reactions to visits predict firms' fundamental performance, but do not link them to future returns, which are central to our study. Our findings differ in large part because we draw signal content from the firms investors choose not to visit, rather than focusing only on visited firms.

Third, the disproportionate allocation of site visits to underpriced firms highlights a novel mechanism giving rise to asymmetric responses to good versus bad news, and dovetails nicely with evidence in Hong, Lim, and Stein (2000) that bad news travels slower than good news. Prior research attributes this tendency for prices to reflect good news faster than bad news to either firms' disclosure patterns (e.g., Kothari, Shu, and Wysocki (2009)) or asymmetric costs of trading (e.g., Johnson and So (2018)). Our study extends these prior findings by highlighting a tilt in the institutional vetting process toward underpriced firms, and thus offers an alternative and non-mutually exclusive explanation for predictability in the cross-section of returns.

Our findings also illustrate that required disclosure of site visits by firms on Shenzhen Stock Exchange serves an important role by signaling information about expected returns. Specifically, because conducting site visits is costly for investors, disclosures of these visits likely serve as a credible signal of underpricing to other investors and thus may spur coordination. In so far as visiting institutional investors are able to implement their trades prior to the deadline to publicly disclose these visits (e.g., within two trading days), these disclosures are unlikely to disincentivize institutions from using site-visits as a means of verifying underpricing. Thus, our findings attest to the potential benefits of these disclosure in other countries, especially within emerging markets similar to China.

Finally, on the practical front, this study provides and validates a simple approach for extracting information from institutional investors' resource allocation decisions. Specifically, we provide a simple characteristic-based model to uncover expected return information embedded in the frequency of on-site investor visits with firms that offers strong predictive power for future returns and changes in firms' fundamental performance.

II. Methodology and Institutional Details

A. Sample Composition and Background Information

Our main analyses examine the link between abnormal investor site visits and the cross-section of future stock returns. Because U.S. firms are not required to publicly disclose these visits, prior studies involving U.S. firms rely on proprietary datasets (e.g., Soltes (2014) and Solomon and Soltes (2015)). To overcome data limitations present for institutional visits to U.S. firms, we study site visits disclosed by firms on the SZSE in China, where firms are required to disclose site visits in a timely fashion. This requirement allows us to study investor site visits for a large sample and cross-section of firms.[2]

Related work by Solomon and Soltes (2015) examines a unique set of proprietary records of all management's one-on-one visits with investors for a specific NYSE firm and shows investors benefit from these visits in the form of more profitable trades. Similarly, using another individual firm, Soltes (2014) shows private visits between analysts and managers complement other public interactions, and spur information production.

Data on investor site visits, stock prices, and firms' fundamentals come from the China Stock Market & Accounting Research (CSMAR) database. Our sample begins in July 2012, which coincides with the SZSE introducing a requirement for listed firms to publicly disclose a summary report on each private meeting within two trading days of the visit date through the

[2]Please refer to Cheng et al. (2016, 2019) and Bowen, Dutta, Tang, and Zhu (2018) for helpful detailed descriptions of these disclosures and further institutional background details.

stock exchange's web portal. Our sample thus includes all disclosed on-site investor visits conducted by SZSE-listed firms from July 2012 through December 2019.[3]

In constructing our sample of investor site visits, we exclude press conferences, road shows, and media interviews. Furthermore, we manually check the original disclosure and delete 905 reported communications by phones, video-calls, or emails to focus our analyses on face-to-face site visits at firms' plants or headquarters.[4] For the firm-month sample merged with price and fundamental data, we require non-negative book equity and market value, fundamental information, and non-zero trading volume on the last trading day of the month. We limit our sample to on-site investor visits participated by at least one institutional investor, which includes both mutual funds and hedge funds.[5]

We intentionally screen out sell-side analyst visits from our sample. We do this for two reasons. First, it places focus on the vetting process directly undertaken by institutional investors, rather than information intermediaries. Second, this focus helps us draw contrast from prior studies that study in-person visits between firms and analysts such as Bowen et al. (2018), Cheng et al. (2016), Han et al. (2018), and Chen, Ma, Martin, and Michaely (2022). In doing so, we also show on-site investor visits subsume the information content of on-site sell-side analyst visits for stock returns.[6] Our final sample consists of 108,874 firm-month observations spanning July 2012 to December 2019.

[Insert Figure 1 approximately here]

Figure 1 Panel A shows the vast majority (88.9%) of investor site visits are publicly disclosed within two trading days of the visit date. To mitigate potential look-ahead bias, we rely

[3]Prior to July 2012, the SZSE required listed firms to disclose information on the dates and brief summaries of private visits in their annual reports. From July 2012, the SZSE required all listed firms to electronically publish a standard visiting report for each investor visit through its web portal, "Hu Dong Yi", at http://irm.cninfo.com.cn/szse/. In addition, Lee and Zhong (2022) document that from 2010, a vast majority of Chinese publicly listed firms began using "Hu Dong Yi" to engage their investors in direct dialogues.

[4]Our results are not sensitive to this choice.

[5]In the robustness tests (Panel A, Appendix B), we present results for four different samples: fund firms (including mutual funds and hedge funds), mutual funds, full sample (including both buy- and sell-sides), and sell-side institutions. Our results are robust to all four samples.

[6]In Table 3 column 8, we show that investor AIV significantly predicts future returns, while sell-side analyst AIV does not when adding the two variables together in the regression.

on the disclosure date rather than the visit date in our forecasting tests.[7] More generally, we map all data based on information publicly available at the end of month m when forecasting returns in month $m + 1$.

Panel B of Figure 1 shows that roughly 22.1$\%$ of site visits consist of one visiting institution, and the median number of institutions per visit is four. The fact that these visits often involve multiple investors visiting on the same day is consistent with institutions relying on correlated signals of underpricing, and firms reducing costs by hosting multiple institutions simultaneously.

[Insert Table 1 approximately here]

Panel A of Table 1 reports key descriptive statistics. The number of investor site visits per year varies during our sample period, with a high of 4,426 visits in 2014, and a low of 2,791 visits in 2019. The number of hosting firms peaks in 2016 at 1,141, with an average of 923 during our sample period. On average, each visited firm hosts three to four site visits per year. There are on average 13 different buy-side institution participants for each visit. In our sample period, the average number of participants per visit has increased from about six institutions in 2012 to about 15 institutions in 2019. Approximately 90$\%$ of our main sample consists of site visits attended by at least one mutual fund. The fact that institutions commonly allocate resources to site visits complements a large body of research showing that communications with firms' managers at investor conferences and road shows resolve information asymmetries, and improve decision making (e.g., Bushee, Jung, and Miller (2011, 2017), Green, Jame, Markov, and Subasi (2014a,b), Soltes (2014), Solomon and Soltes (2015), Subasi (2014), Kirk and Markov (2016), Tang and Zhu (2020), and Chen et al. (2022)).

Furthermore, Panel A of Table 1 reports that 77.4$\%$ of all visits participated by mutual-fund were cases in which the fund had not owned shares of the hosting firm prior to the visit, which we refer to as "non-holder" visits. We determine whether a given mutual fund holds the firms' stocks by examining the latest available mutual fund's holding disclosure before the

[7] We also exclude site visits of which the disclosure date is more than 10 trading days after the reported visit date.

visit date. These results suggest that investor site visits are an important part of the vetting process for institutional investors and commonly take place before the initial investment position is undertaken.

B. Methodology

The first step in our analyses involves estimating abnormal on-site investor visits for each unique firm-month. We use the notation *i* to index firms and *m* to refer to the calendar month in which we estimate firms' abnormal investor visits. We estimate abnormal site visits by identifying discrepancies between realized and expected visit frequencies based on observable proxies for firms' size, liquidity, and past-performance profile. Calculating these discrepancies requires two central inputs: measures of on-site investor visits frequencies and firm characteristics useful in estimating expected visits.

In our main tests, we measure investor site visits as the number of unique visits disclosed by each firm over the trailing three months (i.e., *m*-2, *m*-1, and *m*), to predict returns in *m*+1 and beyond. It is important to note that our empirical tests are designed to avoid look-ahead bias, which are crucial for the interpretation of our findings. Specifically, we calculate the abnormal component of on-site investor visits using monthly regressions to isolate the variation not attributable to firms' size, liquidity, and past performance profile. This approach helps mitigate the fact that institutions naturally skew their attention toward large, easily traded firms, which tend to have better trailing performance.

We use the log of one plus total site visits when estimating firms' abnormal visit frequency.[8] Specifically, we calculate abnormal site visits for firm *i* in calendar month *m* by

[8]In the Internet Appendix Section 4, we show that our results are qualitatively unchanged when using total number of visiting investors instead of the total number of site visits as the determinant model. Additionally, following Cohn, Liu, and Wardlaw (2022), we also show in our Internet Appendix Section 3 that our results are qualitatively unchanged when using raw values of $VISIT$, instead of the $log(1+Y)$ specification, in cross sectional Poisson regressions to calculate AIV.

estimating the following regressions:

$$LNVISIT_{im} = \beta_0 + \beta_1 SIZE_{im} + \beta_2 TURN_{im} + \beta_3 MOMEN_{im} + \beta_4 ROA_{im} + \epsilon_{im}. \tag{1}$$

where $LNVISIT_{im}$ is the log of one plus number of on-site investor visits for firm i in the three months leading up to m. $SIZE_{im}$ is the log of market capitalization in million CNY for month m. $TURN_{im}$ is average trading volume in past 12 months scaled by shares outstanding. $MOMEN_{im}$ is cumulative returns in past 12 months. ROA_{im} is operating income scaled by total assets. All variables are winsorized within each cross-section at 1% and 99$\%$ levels. In robustness tests, we show our inferences are not highly sensitive to the choice of estimation model. For example, Panel B of Appendix B highlights similar inferences when we define $LNVISIT_{im}$ using past six-month or past 12-month time windows. [9]

We define abnormal site visits for each firm-month as the regression residuals (i.e., ϵ_{im}) from estimating equation (1). We use the notation AIV to refer to the abnormal component of site visits, where higher values correspond to firms that have more site visits than expected given their size, liquidity, and past performance profile. Panel B of Table 1 contains the time-series average coefficients from estimating equation (1). Total investor site visits are increasing with contemporaneously measured firm size (t = 28.71), share turnover (t = 4.01), firms' momentum (t = 13.33), and ROA (t = 25.52).

We select the four firm characteristics used in equation (1) for parsimony and computational ease, but recognize that this specification omits other firm characteristics that likely drive some variation in expected site visits. For example, prior research shows that the determinants of on-site investor visits decisions include firm size, market share, profitability,

[9] In Internet Appendix Section 2, to control for persistent firm characteristics such as geographic location and the nature of the business, we also include lagged $LNVISIT$ to our determinants model. In doing so, we continue to find that AIV positively predicts future stock returns. In the robustness tests (Appendix B Panel C), we find that our inferences are robust to alternative determinants models for number of visits, either only using $SIZE$, or using $SIZE$, $TURN$, and $MOMEN$. In an untabulated test, we also find similar results when including past mutual fund holdings as one of the variables in the determinant model.

book-to-market ratio, business segments, listing history, disclosure ratings, etc (e.g., Cheng et al. (2019)). The goal of calculating abnormal site visits is to remove the mechanical component associated with firm characteristics, suggesting that any variable included in calculating abnormal site visits should at least have incremental and statistically significant explanatory power for on-site investor visits.

To shed light on this issue, Figure 2 plots the absolute t-statistics and adjusted R^2 values when iteratively adding firm characteristics to equation (1). The incremental t-statistics for all four variables in our determinant model are above 2. Moreover, the slope of R^2 gradually increases, even after controlling for firm's size. In Panel C of Appendix B, we provide corroborating evidence that the change of controls does not significantly impact the predictive power of abnormal on-site investor visits for future returns.

[Insert Figure 2 approximately here]

Figure 3 reports the fraction of mutual funds that meet before owning the stock (i.e., percentage of "non-holder" visits) by quintile of AIV. We define non-holder visits as cases where a mutual fund visits a firm without holding its shares prior to the visit date. We focus on mutual funds for these tests because, unlike in the US where all institutions whose managing assets above $100mm USD disclose their holdings, Chinese regulators currently only require mutual funds to disclose their holding information.

[Insert Figure 3 approximately here]

To construct Figure 3, we first sort firms into quintiles based on AIV each month. Then within each quintile, we define the percentage of non-holder visits as the number of mutual fund visits for which none of the visiting mutual funds own shares in the firm, divided by the number of mutual fund visits in the past three months. Figure 3 shows that in the high AIV quintile, approximately three-quarters of on-site investor visits occur before the investor takes an initial investment position. These statistics underscore the prevalence with which mutual fund investors visit firms without yet holding a position, suggesting that site visits are a recurring feature of the institutional vetting process.

III. Main Findings

A. Portfolio Tests

Table 2 reports the main results of our paper. Specifically, we show that high AIV firms significantly outperform low AIV firms for both equal- and value-weighted portfolios using raw, market-adjusted, and characteristic-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997). Starting in Panel A, we sort the cross-section firms into quintiles at the end of each month, based on their most recent level of AIV estimated from equation (1). We rebalance quintile portfolios at the beginning of each month to maintain either equal- or value-weights.

[Insert Table 2 approximately here]

Panel A of Table 2 shows that the equal-weighted AIV quintile strategy yields average monthly returns of 114 basis points (t-statistic=5.52), which equates to 13.68$\%$ on an annualized basis. Similarly, AIV strategy returns are 65 basis points per month (t-statistic=2.92) when value-weighted, which annualizes to 7.8$\%$ per year.

To contextualize the results in Table 2, Figure 4 presents average monthly returns to the equal- and value-weighted AIV strategies for each year in the sample. The average strategy returns are generally positive throughout the sample window, including the bull market from July 2014 to May 2015, and the bear market from June 2015 until the end of 2019. Moreover, the distribution of returns appears positively skewed, where the average equal- and value-weighted returns are positive in all but one year in sample window from 2012 through 2019. These distributional patterns mitigate concerns that our results concentrate in a particular period and/or reflect compensation for an unspecified form of risk.

[Insert Figure 4 approximately here]

In Panel B of Table 2, we report the portfolio alpha as well as the factor loadings on each of the Fama and French (2015) five factors. We find that after controlling for five factors, the t-statistics corresponding to AIV strategies generally increase, while yielding similar annualized returns. Notably, the value-weighted strategy has little exposure to standard asset pricing factors aside from the HML value factor. The tests help mitigate concerns that our findings stem from exposure to standard forms of priced risks.

B. Regression Results

In Table 3, we conduct Fama-MacBeth regressions where the dependent variable is the firm's raw returns in month $m+1$ (denoted RET_{m+1}) while controlling for a host of variables nominated by the literature. To facilitate interpretation, all explanatory variables are standardized as zero mean and one standard deviation within each calendar month.

[Insert Table 3 approximately here]

Column 1 of Table 3 shows the raw number of on-site investor visits, $LNVISIT$, does not have predictive power for future returns (t=1.23). The insignificance of the raw visit count is consistent with site visits containing a mechanical component unrelated to expected returns. By contrast, columns 2 through 8 highlight a robust positive relation between AIV and future returns across all seven specifications.

The level of abnormal analyst coverage, $ATOT$, introduced in column 3 is a particularly important control variable to distinguish our findings from Lee and So (2017). As shown by Lee and So (2017), firms with abnormally high analyst coverage subsequently outperform firms with abnormally low coverage. The incremental predictive power of AIV relative to abnormal analyst coverage helps mitigate concerns that our results are driven by analysts spurring site visits through their coverage decisions.

Column 3 also controls for lagged size (i.e., market capitalization), book-to-market, quarterly return on equity, asset growth, turnover, *MOM1*, short-term return reversals, using firms' stock return in month m-1 (Jegadeesh and Titman (1993)), and *MOM12*, a medium-term price momentum variable, defined as the focal firm's trailing 12-month return ending in month m-1 (Chan, Jegadeesh, and Lakonishok (1996)). The t-statistic for AIV remains above three across all specifications.

Another goal of Table 3 is to distinguish our findings from those in Cheng et al. (2019), which shows that signed stock returns around site visits are positively correlated with firms' forthcoming earnings news. In column 4, we include $AVGSAR$ as one of our control variables, which we define as the average of cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for on-site investor visits that happened in past three months, following Cheng et al. (2019). The results in column 4 indicate that although future earnings news is associated with signed stock returns around on-site investor visits, the signed stock returns around these visits do not predict future returns.

Columns 5 through 7 include controls for levels of, and changes in, mutual fund holdings to mitigate concerns that our results reflect price pressure from institutions initiating positions. We include three measures of institutional holdings. First, $HOLDPCT$ is the percentage of shares held by mutual funds based on the latest available semiannual or annual fund reports prior to the portfolio formation date. $\Delta HOLDPCT(LAG)$ equals the changes in mutual fund holding percentage based on the two latest available semiannual or annual reports prior to the portfolio formation date. $\Delta HOLDPCT(FUT)$ equals the change in mutual fund holding percentage from the last semiannual period to the current semiannual period. [10] Columns 5 to 7 show the return predictive power of AIV remains virtually unchanged after controlling mutual fund holdings. A striking finding in column 7 shows similar inferences even when intentionally introducing look-ahead bias by controlling for future changes in fund holdings. These tests suggest our findings are unlikely driven by mechanical price pressure from institution visit with firms before ramping up their holdings.

Finally, in column 8, we compare the predictive power of buy-side site visits (i.e., AIV) with visits arranged by sell-side analysts. To capture the role played by sell-side analysts, we introduce and control for AIV_NOFUND, which captures abnormal visits likely by sell-side

[10] Let's take a site visit of fund f to firm i in May 2021, or AIV measured from April to June, 2021, as an example. In this case, $\Delta HOLDPCT(FUT)$ equals the holdings of fund f to firm i on June 30, 2021 (reported in August 2021), minus the holdings on December 31, 2020 (reported in March 2021). Whereas, $\Delta HOLDPCT(LAG)$ equals the holdings of f to i on December 31, 2020 (reported in March 2021), minus the holdings on June 30, 2020 (reported in August 2020).

analysts (i.e., not fund market participants). We measure AIV_NOFUND analogous to AIV but focus on visits for which none of the reported visitors appear to be from an investment fund. Consistent with Appendix B Panel A, column 8 of Table 3 shows that AIV robustly predicts future returns, whereas abnormal visits driven by sell-side analysts (AIV_NOFUND) do not incrementally predict the cross-section of firms' returns. These findings suggest institutional investors convey expected return information through their resource allocation decisions, distinct from the role played by sell-side analysts.

Having established that abnormal on-site investor visits predict one-month-ahead returns, our next analyses examine the persistence of this predictive relation. Figure 5 Panel A shows that lagged values of AIV also predict equal- (value-) weighted returns for up to a ten (six)-month lag and gradually become insignificant with longer lags. These findings show the sign of the strategy returns does not immediately reverse when using lagged signals and thus mitigate concerns that the predictive power stems from transitory price pressure that immediately reverses in subsequent months. Similarly, to the extent our results are driven by transitory price pressure from visiting institutions initiating positions, we would expect to observe return reversals over longer holding periods.

[Insert Figure 5 approximately here]

Figure 5 Panel B plots the twelve-month cumulative returns to the AIV hedge portfolio after portfolio formation. Consistent with the results in Figure 5 Panel A, equal-weighted cumulative returns continue to drift upward for an additional ten months and value-weighted return for an additional six months. Moreover, we find no sign of a return reversal over the next 12 months, suggesting our results reflect a delayed reaction to fundamental information rather than transitory price pressure.

In Table 4, we detail the prevalence and predictive power of within firm changes in abnormal investor site visits. Panel A reports transition matrix showing how many firms in the highest quintile of abnormal investor visits in quarter q remain in the highest quintile in q+1. The results show 45.4% of firms in the highest quintile of abnormal investor visits in quarter q remain in the highest quintile in q+1, and 55.8$\%$ of firms in the lowest quintile of abnormal investor visits in quarter q remain in the lowest quintile in q+1, suggesting the abnormal visits display significant within-firm variation over time.

[Insert Table 4 approximately here]

Panel B reports equal-weighted DGTW-adjusted portfolio returns based on abnormal investor visits (AIV) and changes in abnormal investor visits (ΔAIV). All stocks are equally weighted within a given portfolio (5×3), and the portfolios are rebalanced every calendar month to maintain equal weights. Panel B shows the positive returns among high AIV stocks concentrate in cases where the abnormally frequent visits coincide with an increase in abnormal investor visits relative to the prior quarter (i.e., the highest tercile of ΔAIV), and vice versa. A conditional strategy that bets on firms with high values of both AIV and ΔAIV, and bets against firms with low values of both AIV and ΔAIV, yields a monthly average return of 0.78$\%$ (t=5.58), which is an 18$\%$ increase relative to the unconditional equal-weighted DGTW-adjusted AIV strategy return (0.66$\%$) reported in Table 2. These results suggest that abnormally frequent site visits are particularly informative of underpricing when they coincide with a recent uptick in site visits, rather than as part of a routine schedule of visits.

IV. Underlying Mechanisms

This section focuses on the mechanisms underlying how investors identify underpriced firms. In doing so, we also provide novel evidence on the nature of information investors accrue that helps justify the cost of visiting firms.

A. Cost of Investor Visits

Our first tests examine the hypothesis that institutions incur costs to visit firms as a means to identify underpriced companies. Since institutions incur fixed costs to learn about firms, we expect the predictive power of AIV is higher when institutions are visiting firms for which they do not yet own the firm's shares, rather than as a means of continued dialogue with managers from previously established positions. We conduct these tests by running our main return forecasting tests for subsamples of visits based on whether at least one of the visiting institutions is a mutual fund that did not own the firm's shares prior to the visit (i.e., $Non\text{-}holder$=1). Consistent with our hypothesis, Panel A of Table 5 shows the positive relation between AIV and future returns concentrates in cases where $Non\text{-}holder$=1. Related tests in Panel A of Table 5 condition on whether site visits correspond to a newly visited firm. Specifically, $Initial$ = 1 when the investor has not visited the firm in the past six months, and zero otherwise. Because initial visits likely pose greater costs than follow-up visits (e.g., initial visit investors require making new contacts at the firm), we expect strategy returns are more pronounced for abnormal initial visits. Panel A shows our return results are indeed stronger for initial compared to follow-up visits, consistent with investors incurring higher information gathering costs when they anticipate greater underpricing.

[Insert Table 5 approximately here]

Table 5 Panel A also shows that our return results are stronger when investors incur higher travel costs.[11] We utilize latitude and longitude data on Baidu Map API to measure the travel time between investors and firms, consistent with previous literature (e.g., Tian (2011)).[12] This allows us to obtain the travel time of the optimal route for that visit, which serves as an input of travel cost proxy. For these tests, we exclude local visit observations, as site visits are not the primary drivers of local investors' advantage (Malloy (2005) and Bae, Stulz, and Tan (2008)).

We measure travel costs to capture the time and resources that investors allocate toward site visits. Specifically, we calculate Travel Cost (TC) as the travel time for a specific visit minus

[11] We would like to thank the referee for this suggestion.

[12] We employ the Baidu Maps API to input the latitude and longitude of the locations of both the fund and the listed firm for a single site visit. Baidu Map provides a powerful route planning API (https://api.map.baidu.com), and offers route planning services covering both domestic and international regions. This API supports various modes of travel such as airplanes, high-speed trains, cars, and cycling. In the route planning API, users provide the latitude and longitude coordinates of any two locations, and Baidu Map provides the traffic route planning between these two locations. It compares the time consumption of various transportation routes such as airplanes, high-speed trains, and cars. By setting the parameter for the number of routes (corresponding item "page size") to 1, the API will by default return the optimal route with the shortest duration. Furthermore, users can extract the travel time of this optimal route (corresponding item "duration").

the average time for all visits in the previous three months for a given firm. We then construct AIV for subsamples of visits based on whether the visiting institutions incur higher travel costs than the median of all visits for other firms in month m, in which case we define $HighCost$ = 1 and all other visits as $HighCost$ = 0.[13]

B. Hosting Firm Characteristics

In columns 2 through 5 of Table 5 Panel B, we provide related evidence that abnormal investor visits are more informative of future returns among firms subject to greater information asymmetries. These tests focus on the interaction effect between AIV and four dummy variables that identify firms with poor information environments: low analyst coverage, low institutional ownership, recent losses, and small firms. Columns 2 through 5 of Table 5 Panel B show the coefficient estimates on all four interaction terms are significantly positive, consistent with investors using site visits to gain an investment advantage, which naturally confers a larger advantage when the information environment is poor.

In columns 6 and 7 of Table 5 Panel B, we provide evidence that our main results are more pronounced when there is less public attention coinciding with the site visits. We focus on the interaction effect between AIV and two proxies of investor attention based on analyst and media reactions, i.e., analyst forecast revision ($Revision$), and media and analyst attention ($Attention$). Columns 6 and 7 of Table 5 Panel B show that the coefficient estimates on both interaction terms are significantly negative, which is consistent with our return prediction results being driven by investors having limited attention and only gradually reflecting the information content of site visits into stock prices.

[13] As an illustration of our methodology, consider a site visit event: Tianhong Asset Management incurred 5.5 hours of travel time to visit Tagen Group Co., Ltd. on January 15, 2015. Meanwhile, the average travel time for Tagen Group Co., Ltd. from October to December 2014 was 4 hours. In this case, the TC would be 1.5 (5.5 minus 4). Then, we compare this TC (equals 1.5) with the median TC (equals 2.85) of all visits for other firms in January 2015. Since TC for this visit is lower than the median (1.5 < 2.85), we assign it as $HighCost$ = 0.

C. Abnormal Visits Conditioning on Trading Volume

In Table 6, we show that the predictive power of AIV for future returns concentrates among neglected firms as indicated by lower trading volumes. Panel A of Table 6 shows that a portfolio that buys stocks with high abnormal visits and low abnormal turnover earns 0.59% per month. Similarly, a portfolio that shorts stocks with low abnormal visits and high abnormal turnover earns 0.90% per month. Thus, combining these strategies yields a DGTW-adjusted hedge return of 1.49% per month, which is nearly double the return corresponding to the unconditional AIV strategy.

[Insert Table 6 approximately here]

In Panel B of Table 6, we present returns to our AIV strategy conditioned on absolute three-month momentum ($AMOM3$). We expect that if a firm's past absolute momentum is large, site visits may be reaction-based, with institutions visiting the firm to understand the significant changes in past returns, and such visits should be less informative than information-based visits. The findings align with our expectations: the portfolio with high abnormal visits and mid $AMOM3$ achieves the highest future DGTW-adjusted returns of 0.64% per month, while the portfolio with the lowest abnormal visits and highest $AMOM3$ earns the lowest future DGTW-adjusted returns of -0.39% per month. Notably, a hedge portfolio that buys stocks with high abnormal visits and low $AMOM3$ and sells stocks with low abnormal visits and high $AMOM3$ generates a DGTW-adjusted hedge return of 0.89% per month.

D. Forecasting Fundamental Performance

In Table 7, we provide evidence that AIV likely positively predicts future returns because visited firms tend to subsequently report positive earnings announcement news. Specifically, Table 7 documents the predictive power of AIV for four measures of firms' one-quarter ahead fundamental performance: (1) standardized unexpected earnings (SUE), the year-over-year change in quarterly operating income scaled by the standard deviation of unexpected earnings over the eight preceding quarters; (2) earnings announcement returns (SAR), firms' size-adjusted return on their quarterly earnings announcement date; (3) forecast error (FE), firms' reported EPS minus consensus forecast at the end of fiscal year divided by total assets per share; and (4) analyst forecast revision (REV), the change in consensus forecast measured at the end of fiscal year, divided by total assets per share.

[Insert Table 7 approximately here]

Panel A of Table 7 highlights a strong positive relation between AIV and all four measures of firms' subsequently reported fundamental performance. These evidence suggests our results stem from institutions anticipating changes in firms' fundamentals and pursuing visits with ascending firms. Because these measures proxy for predictable errors in investors' expectations over firms' performance, these tests help mitigate concerns that our results are driven by compensation for unmodeled forms of risk.

Next, we examine stock price reactions around subsequent earnings announcements. This approach is widely used in the literature (see, for example, Bernard and Thomas (1989), Chopra, Lakonishok, and Ritter (1992), La Porta, Lakonishok, Shleifer, and Vishny (1997), Gleason and Lee (2003), and Engelberg, McLean, and Pontiff (2018)). The idea is intuitive: if an anomaly is associated with mispricing, then it will be stronger in the earnings announcement window, as the release of these earnings helps to correct prior misconceptions about firms' expected cash flows. In contrast, if an anomaly is driven by changes in underlying risks, then the subsequent returns should accrue more evenly over subsequent periods.

Panel B of Table 7 shows that a substantial portion of AIV-strategy returns concentrate around firms' future earnings announcement dates. Table values represent mean raw and size-adjusted returns for each hedge strategy realized over one-day- and three-day-windows centered on the next earnings announcement and all earnings announcements within the next six months. We find that strategy returns are 3.6 to 4 times larger during an earnings announcement than on non-announcement days.[14] These findings suggest that the predictive power of AIV

[14] Collectively, 2.9 (3.2) percent of the raw (size-adjusted abnormal) returns realized over the next six months are earned on the next earnings announcement day. Assuming expected returns do not vary daily, we expect 0.8 percent (=1/127) of the abnormal return to occur over 1 trading day.

stems from investors seeking visits with underpriced firms, and the underpricing correcting around future earnings release dates.

E. Alternative Explanation: Information Risk

A potential alternative explanation of our main findings is that investors endogenously chose to visit firms with opaque information environment. Under this alternative, AIV can be viewed as a proxy for information risk that commands higher expected returns as compensation. [15] To mitigate this concern, we conduct the two tests below to show that the AIV return predictability is unlikely driven by information risk. We present the results in Internet Appendix Table A1.

Table A1 Panel A reports the Pearson correlations between AIV and measures of information risk, i.e., volume synchronized possibility of informed trading ($VPIN$) and time-weighted bid-ask spread ($SPREAD$) (Easley, López de Prado, and O'Hara (2012) and McInish and Wood (1992)). If the information risk hypothesis holds, we should find a positive correlation between AIV and other information risk proxies. Table A1 Panel A shows that both $VPIN$ and $SPREAD$ are significantly negatively correlated with AIV, which is inconsistent with potential concerns that investors tend to visit firms with higher information risk.

In Table A1 Panel B, we also show that the return predictability of AIV remains robust after including information risk. We conduct Fama-MacBeth regressions where the dependent variable is the firm's raw returns in month m+1 (denoted RET_{m+1}) while controlling for a host of variables nominated by the previous literature (see column 6 of Table 3 of main text) and information risk, proxied by $VPIN$ ($SPREAD$). The fact that the return predictability of AIV holds in these tests again suggests that our findings are unlikely explained by information risk.

[15] We would like to thank the referee for this suggestion.

V. Site Visits, Fund Holdings, and Exogenous Travel Restrictions

In this section, we investigate how investor visits vary with fund holdings. We also examine whether and how site visits were impacted by exogenous restrictions on travel and the implications for funds' performance.

A. Site Visits and Fund's Portfolio Management Behavior

In Table 8, we examine changes in institutional investors' holdings surrounding abnormal visits. These tests are motivated by the idea that institutions use site visits to identify underpriced firms and thus are more likely to purchase shares following their visits. To conduct these tests, we define Δ*HOLDPCT(FUT)* as the change in mutual fund holding percentage from the last semiannual period to the current semiannual period. Consistent with our prediction, Panel A of Table 8 shows that AIV precedes significant increases in mutual fund holdings of the visited firm. Moreover, these findings appear remarkably robust to adding various controls including past holdings and lagged changes in holdings, suggesting that institutions use information from site visits as a precursor to purchasing shares.

[Insert Table 8 approximately here]

In Panel B of Table 8, we decompose Δ*HOLDPCT(FUT)* into changes in holdings among visiting funds vs. non-visiting funds. To the extent that visits convey an information advantage, we expect that the positive link between AIV and Δ*HOLDPCT(FUT)* concentrates among visiting funds relative to non-visiting funds. Empirically, we define visiting funds as those that conduct visits to a focal firm in the past six months and non-visiting funds as those funds that do not visit a focal firm in the past six months. Consistent with our hypothesis, we find a strong disparity across the two groups. Specifically, we find that the holdings of visiting funds increase with AIV, but holdings for non-visiting funds decrease holdings with AIV. These results indicate that visiting institutions appear to buy shares from non-visiting institutions, consistent with in-person visits spurring ownership changes by conferring visiting institutions with an information advantage regarding firm value.

B. Site Visits, Fund Performance, and Exogenous Restrictions on Travel

In our final tests, we explore how site visits were impacted by exogenous restrictions on travel and the implications for funds' performance. These tests are motivated by the idea that site visits confer an information advantage by allowing investors to evaluate firms up-close and in-person. However, we expect that the travel restrictions deprived investors of this information advantage and, moreover, disproportionately harmed investors that relied heavily on site visits to make investment decisions. To conduct these tests, we extend our sample until December 2021 such that it includes the period of COVID-19 when in-person visits are likely most restrictive.

Figure 6 plots on-site and online investor visit frequencies before and after the pandemic. Panel A of Figure 6 shows that the percentage of on-site investor visits in total visits drop dramatically in the first quarter in 2020, and then gradually recover. In the same vein, Panel B shows that in-person site visits were replaced by online visits.

[Insert Figure 6 approximately here]

In 2020 and 2021, about 50% of site visits are conducted online. However, we find that online abnormal investor visits do not have return predictability. This is consistent with our previous hypothesis that the informativeness of site visits increases with visit costs. These findings also dovetail nicely with our findings that visiting funds benefit from observing firms' operations in person.

Next, in Table 9 Panel A, we examine the relation between fund future performance and the frequency of the fund firm's site visits. α^{4F}_{m+1} is the fund's future one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations estimated using the preceding 24 monthly fund returns. *LNVISIT_FUND* is the log of one plus the number of site visits from mutual funds in the past one month.[16] Following Bai, Tang, Wan, and Yüksel (2022), we include controls for funds' trailing twelve month cumulative return (*RET*), return volatility (*VOL*), and normalized net flow (*FLOW*). We also control for the log of mutual fund's total net asset (*SIZE*), the log of mutual fund's age since inception (*AGE*), and the sum of management fee rate and custodian fee rate (*EXPENSE*).

[Insert Table 9 approximately here]

In all of the seven columns, the coefficients of *LNVISIT_FUND* are positively related to fund alpha and are highly significant, incremental to controls. In general, we find that fund performance is positively related to the number of the fund's visits of listed firms, which is consistent with firms gaining an advantage in identifying mispriced firms when allocating greater resources towards visiting candidate firms.

The outbreak of COVID-19 imposes exogenous restrictions on traveling and may impede institutional investors from collecting information through site-visits. Panel B estimates the impact of such exogenous travel restrictions on fund performance, especially those funds that rely heavily on site-visits. *SiteVisit_Intensity* is measured as the log of one plus the average number of site-visiting for specific fund firm in the pre-COVID era (i.e., from January 2015 to January 2020). We also create an indicator variable, *postFeb2020*, that equals one starting in February 2020. We chose February 2020 as the start date for travel restrictions because the lockdown policy in China began with the city of Wuhan on January 23, 2020. Given this occurs toward the end of the month, we believe it is reasonable to assume in-person visits are likely restrictive within China starting from February 2020 due to the government's epidemic prevention and control policies. *SiteVisit_Intensity* × *postFeb2020* is an interaction term of the two variables.

In Table 9 Panel B, we find that the interaction term is significantly negative, which shows that the negative impact of COVID-19 is more severe for mutual funds that rely more heavily on site visits before the onset of the pandemic. In untabulated tests, we find similar inferences if we use March 2020 or January 2020 as alternative start dates for the beginning of travel restrictions.[17]

[16] We would like to thank the referee for this suggestion.

[17] We thank the editor for raising up the question that why we use Feb 2020 as the start of the lock-down, while the World Health Organization (WHO) declared a global pandemic in March 2020 whereas the sign of COVID-19 (unknown at the time) first appeared in late 2019.

These findings are consistent with funds gaining an information advantage through site visits but that travel restrictions brought on by COVID-19 disproportionately harmed funds that rely on visits in their investment process. As a result, our findings help illustrate how disruptions to the economy and travel shape institutional investor performance and market outcomes by impacting investors' ability to access information.

VI. Conclusion

In this study, we examine institutional investors' resource allocation decisions through the lens of site visits with firms. We do so by decomposing on-site investor visits into an expected component based on observable firm characteristics and an abnormal component, which we show has strong predictive power for returns. Our findings suggest institutional investors disproportionately allocate resources to such visits with underpriced firms, and commonly rely on these face-to-face interactions to calibrate arbitrage opportunities prior to investing.

Abnormally frequent site visits also coincide with increased holdings among visiting institutions and improvements in firms' fundamental performance, consistent with institutions using site visits as a means to gain an information advantage regarding underpriced firms. Finally, we show institutions that conduct more site visits tend to earn higher alphas but were disproportionately harmed by restrictions related to the COVID-19 pandemic. Taken together, our study provides novel evidence regarding how investors form beliefs over future stock returns and the time-consuming process investors commonly undertake when forming portfolios.

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Appendix A. Interview Evidence on Investor Visits

To better understand the relation between on-site investor visits and firms' future performance, we interviewed three fund managers, three sell-side analysts, and three Investor Relation (IR) managers. To promote consistency, we followed a strict interview protocol that asked the same set of open-ended questions in the same order across each different type of interviews. The interviews enriched our understanding on why these visits are important to investors, analysts, and listed firms.

Our first set of interviews centered on three fund managers from a China top ten mutual fund headquartered in Beijing. To gain a broader understanding of site visits, we spoke with three fund managers specializing in different industries: pharmaceuticals, automobile, and intelligence manufacturing.

The fund managers' answers to our questions were quite consistent despite the fund managers specializing in different industries. All three stated that face-to-face site visits play an important role in dictating portfolio allocation decisions. These visits serve in both finding, and confirming potential mispricing.

Due to the importance of site visits, the fund managers we spoke with reported spending roughly 40-50% of total work hours visiting listed firms. One fund manager described that he conducted on average 3 visits each month and more than 30 visits each year. The amount of time committed to these visits is striking and suggests that institutions incur substantial costs to identify underpriced firms.

The fund managers we spoke with also noted they conducted both scheduled and unscheduled on-site investor visits.[18] They gave several motivations for those need-based visits, including: (1) gathering qualitative information that supplements their private information, which is very important in forming investment decisions; (2) building relations with management of the key firms in their portfolio to bolster information exchange.

[18] In 2006, the SZSE issued Fair Information Disclosure Guidelines, stating that SZSE-listed firms should not disclose material nonpublic information to participants during on-site investor visits.

The fund managers also mentioned that a sudden increase in on-site investor visits most likely stems from underpricing, rather than a desire to confirm overpricing. The fund managers reported that they would sell the stock directly if there is bad news rather than attempting to coax managers into divulging bad news via visits. This pattern is also consistent with anecdotal evidence. For example, an article from Sohu Finance reported that once a firm is under CSRC investigation, institutions stop visiting the firm immediately.[19]

While, for sell-side analysts, they reported that information gathered from site visits has important influence to their following stock recommendations. Unlike fund managers, they roughly spent 15%-25% of their total time and energy on site visits.

Finally, we interviewed three IR managers from different listed firms. They confirmed that the vast majority of these visits are requested by institutions, rather than initiated by the firms. Firms seek to accommodate all requests by institutions for private site visits. Collectively, their statements are consistent with fund managers visiting firms to calibrate expected returns.

[19]Please refer to link: https://www.sohu.com/a/122545169_377183.

Appendix B. Robustness of Abnormal Investor Visits Strategy

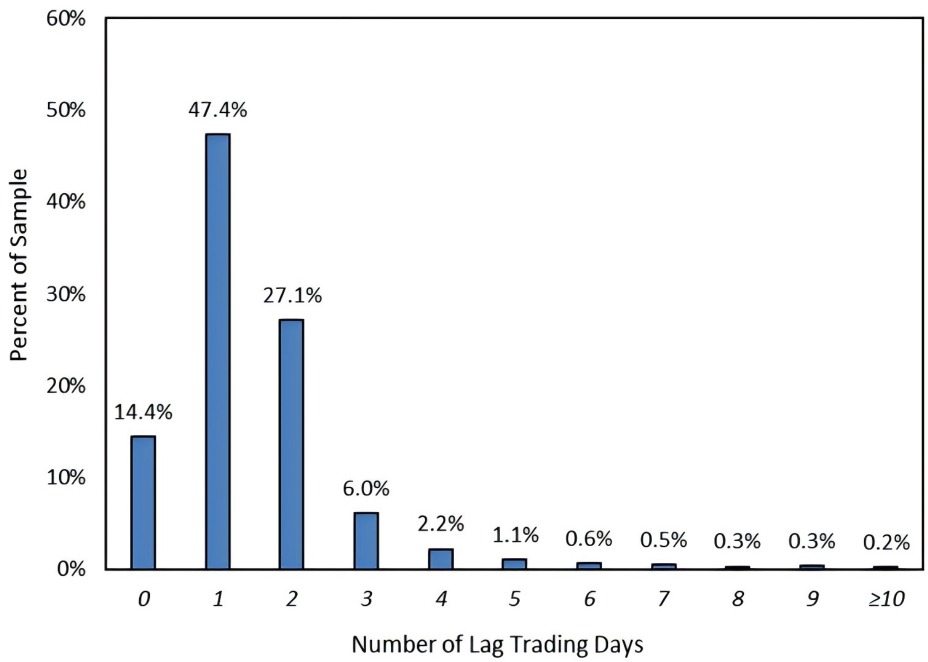
The table presents the results of four sets of robustness checks for abnormal investor visits strategy. Panel A uses different sample requirements for the visitors of the visits. The first requires that at least one visitor is from fund firms (i.e., the default measure in the main analysis which includes mutual funds and hedge funds), the second uses site visits that at least one visitor is from mutual fund firms, the third uses visits which include visitors from both buy-side and sell-side, and the fourth requires that no visitor is from fund firms. Panel B uses different data requirements. The first requires firms to have at least one investor visit in past six months, and the second extends to 12 months. Panel C uses different determinant models to calculate abnormal investor visits. The first uses *SIZE* while the second uses *SIZE*, *TURN*, and *MOMEN*. See Panel B of Table 1 for the model description. Panel D reports results that exclude the smallest 10% or the most illiquid stocks. The right columns report the equal-weighted (EW) and value-weighted (VW) returns of the hedge portfolio that, each month, buys (shorts) stocks with abnormal investor visits in the highest (lowest) quintile. Both raw returns and Fama French 5-factor alpha are included. *# of visits* is the number of visits used in the analysis. *Avg. N* is monthly average number of stocks in the hedge portfolio.

	# of Visits	Avg. N	EW (%)		VW (%)	
			Raw	*Alpha*	*Raw*	*Alpha*
Panel A: Data Requirements for Visitors						
At least one visitor from fund firms	27,931	250	1.14	1.02	0.65	0.71
			(5.52)	(7.86)	(2.92)	(3.84)
At least one visitor from mutual fund	25,380	250	1.11	1.02	0.64	0.74
			(5.25)	(7.32)	(3.00)	(3.82)
At least one visitor from either buy-side or sell-side	52,198	250	1.04	0.98	0.70	0.77
			(5.41)	(7.03)	(3.61)	(4.22)
No visitor from fund firms	24,267	250	0.86	0.55	0.52	0.34
			(3.42)	(3.19)	(2.95)	(2.39)
Panel B: Data Requirements for *LNVISIT*						
At least one investor visit in past 6 months	27,931	251	1.22	1.10	0.81	0.90
			(5.24)	(6.83)	(3.32)	(4.16)
At least one investor visit in past 12 months	27,931	252	0.94	0.92	0.60	0.72
			(3.37)	(4.36)	(2.15)	(2.99)
Panel C: Determinant Models to Calculate *AIV*						
SIZE	27,931	250	1.24	0.96	0.69	0.70
			(3.62)	(4.13)	(2.40)	(2.87)
SIZE, TURN, and MOMEN	27,931	250	1.32	1.14	0.74	0.77
			(5.53)	(7.51)	(2.98)	(3.80)
Panel D: Exclude Micro or Illiquid Stocks						
Exclude the smallest 10% stocks	27,132	225	1.01	0.93	0.60	0.66
			(4.92)	(7.01)	(2.73)	(3.59)
Exclude the most illiquid 10% stocks	27,287	225	1.08	0.96	0.60	0.64
			(5.40)	(7.61)	(2.71)	(3.49)

Figure 1. Description of On-site Investor Visits

Panel A plots percentage of sample that have n (n = 0, 1, 2, . . . , 9, >=10) lagged days between on-site investor visits' visit date and disclosure date. Since July 2012, the SZSE has required listed firms to timely disclose site visits on the public investor relationship platform (http://irm.cninfo.com.cn/szse/). Panel B plots percentage of sample that have n (n = 1, 2, . . . , 10, >10) visitors in an on-site investor visit. The sample consists of 27,931 on-site investor visits spanning July 2012 to December 2019.

Panel A: Number of Trading Days Between Visits and Public Disclosures



Panel B: Number of Visitors per Visit

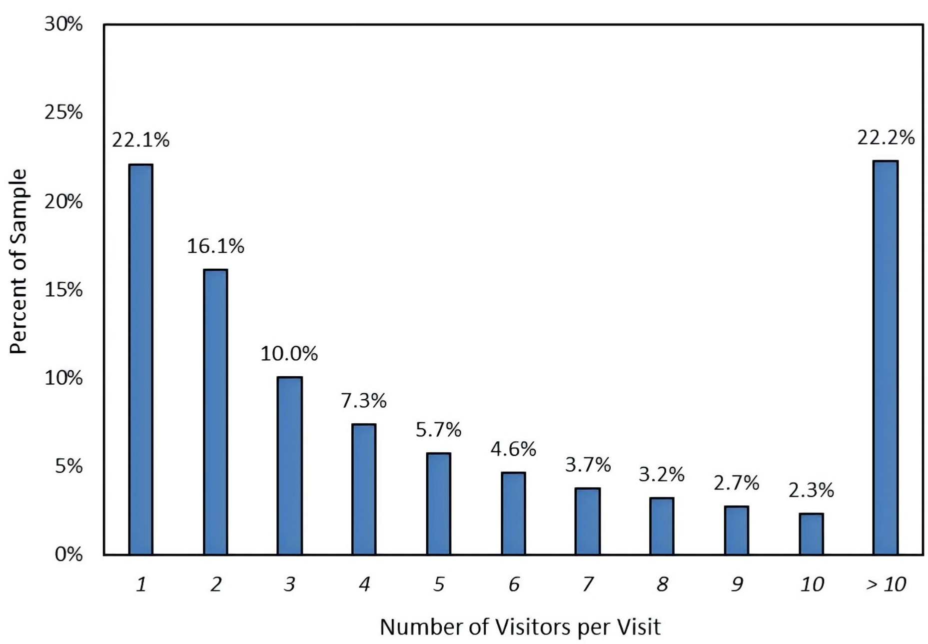


Figure 2. On-site Investor Visits and Firm Characteristics

The figure contains cumulative adjusted R-squared and multivariate t-statistic across regressions of on-site investor visits that iteratively add firm characteristics. Reported values reflect time-series averages of monthly regression results. The reported adjusted R-squared values reflect the explained variation in on-site investor visits after cumulatively adding the variables listed, such that the first value reflects the adjusted R-squared when only including firm size and the last value reflects the adjusted R-squared from including all four listed firm characteristics. Similarly, the reported t-statistics reflect regression results from iteratively adding the firm characteristics listed. See Panel B of Table 1 for the model description. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

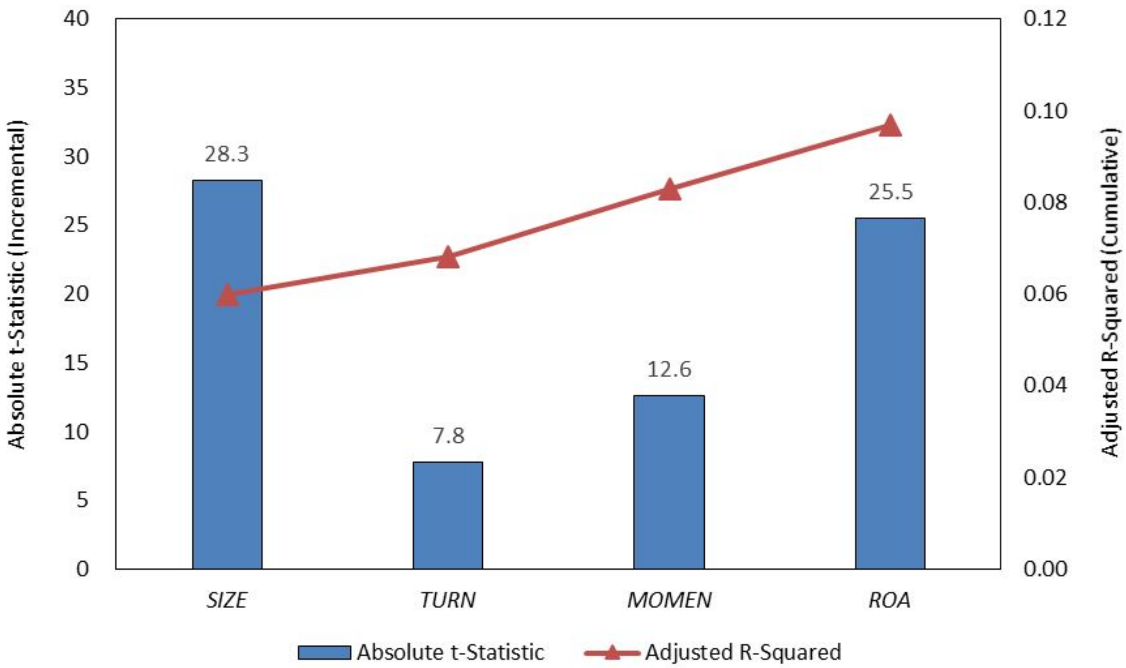


Figure 3. Percentage of Non-Holder Visits in Mutual Fund Visits

This figure contains the fraction of mutual funds that meet firms before owning the stock (i.e., percentage of non-holder visits) by quintile of abnormal on-site investor visits (*AIV*). To derive the percentage of non-holder visits, in each month, we first assign firms into quintiles based on abnormal on-site investor visits, then for each firm, we define the percentage of non-holder visits as the number of mutual fund visits that no mutual fund visitor(s) has (have) previous holding of the visited firm's shares, divided by the number of mutual fund visits in the past three months. The figure shows the time-series average value of non-holder visits percentage for each group. Mutual fund holding information is from the latest available semiannual and annual reports of mutual fund before the visits. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

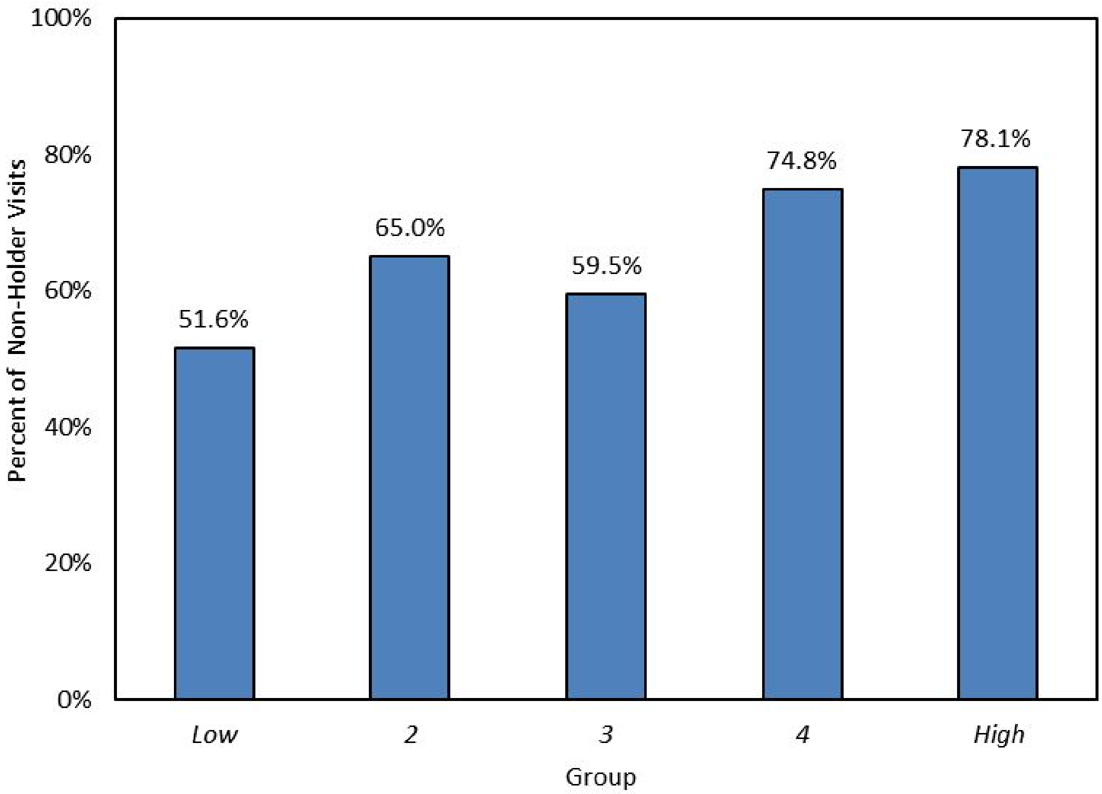


Figure 4. Monthly Average Hedge Portfolio Returns

The figure plots average monthly hedge portfolio returns within each year based on abnormal investor visits (*AIV*). Abnormal site visits is the residual from a monthly regression of log one plus number of site visits in the past three months regressed on firm's circulation market cap, average monthly turnover in past 12 months, cumulative returns in past 12 months, and return on total asset. The strategy is implemented at the end of each calendar month m and held for one month by ranking firms into quintiles of abnormal investor visits and taking a long (short) position in firms within the highest (lowest) quintile. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

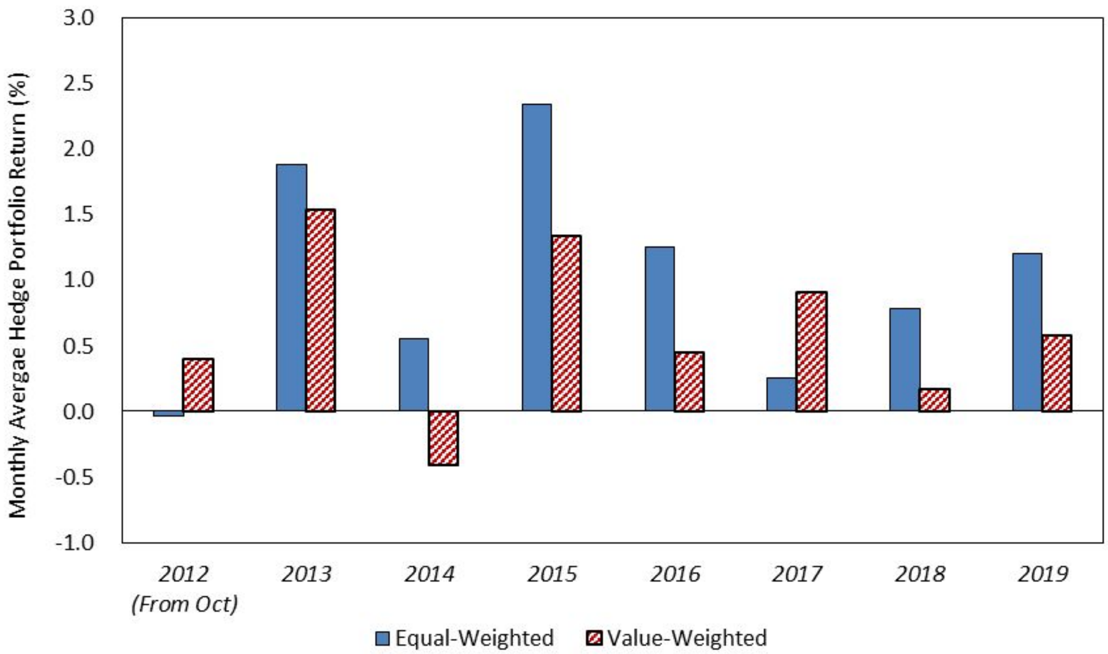
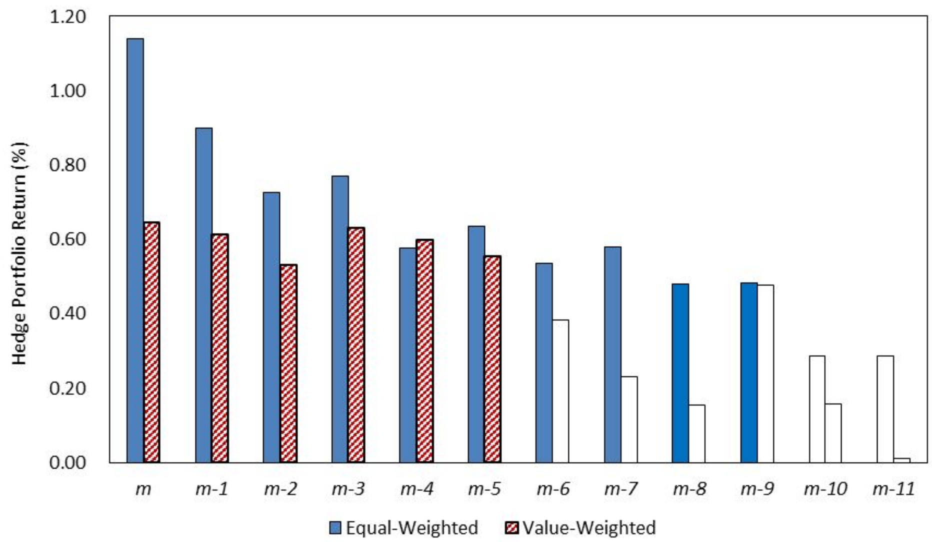


Figure 5. Decay of Hedge Portfolio Returns

Panel A plots monthly returns from the abnormal investor visits strategy using multiple lags between the measurement of investor visits and the monthly returns. Returns are measured in month m+1. The figure illustrates quintile strategy returns measuring abnormal investor visits in months m to m-11. The strategy is implemented at the end of each calendar month m and held in the next month by ranking firms into quintiles of abnormal investor visits and taking a long (short) position in firms within the highest (lowest) quintile. Shaded bars indicate that the reported strategy return is significant at the 5% level. Panel B depicts the time-series average of cumulative returns for next 12 months. The strategy is implemented at the end of each calendar month and held for 12 months by ranking firms into quintiles of abnormal investor visits and taking a long (short) position in firms within the highest (lowest) quintile. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

Panel A: Returns to Lagged Abnormal Investor Visits



Panel B: Time-Series Average Cumulative Returns

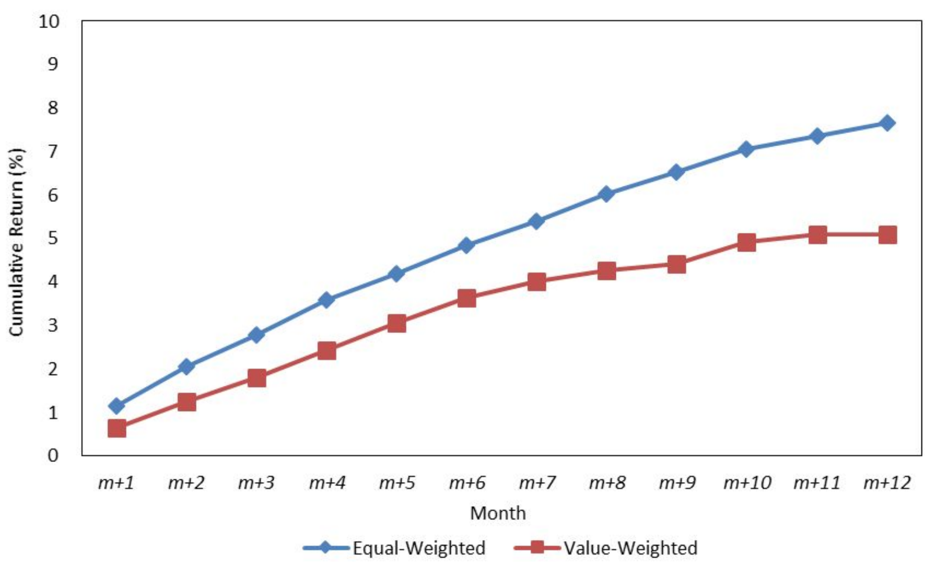
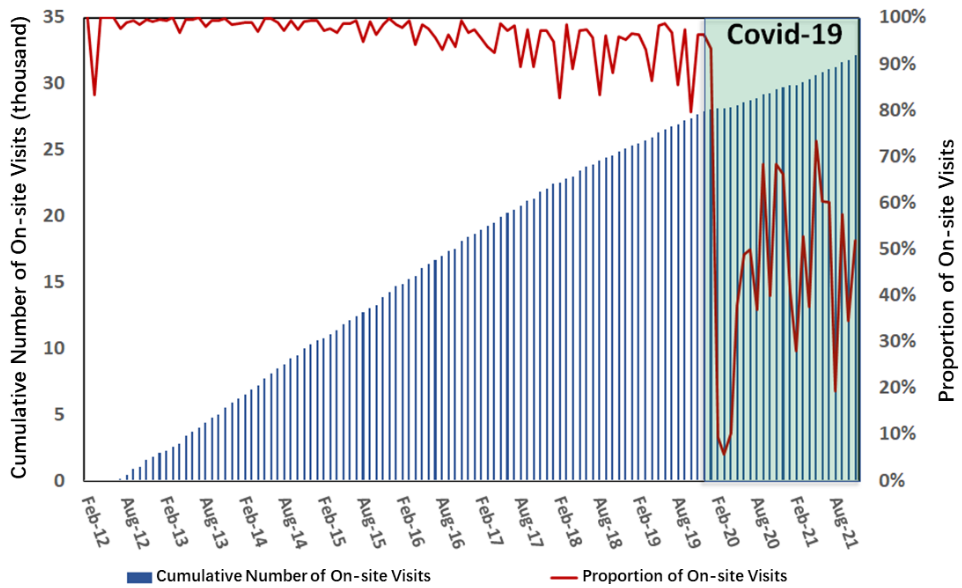


Figure 6. On-site and Online Investor Visits before and after Travel Restrictions

Panel A plots accumulate number of site visits (blue bars) and proportion of site visits in total site visits (red line) for each month. Panel B plots the number of site visits (blue line) and online visits (red line) for each month, respectively. The green translucent windows indicate the outbreak of COVID-19. The sample for this analysis covers the period July 2012 to November 2021.

Panel A: The Impact of Travel Restrictions on On-site Visits



Panel B: On-site Visits vs. Online Visits

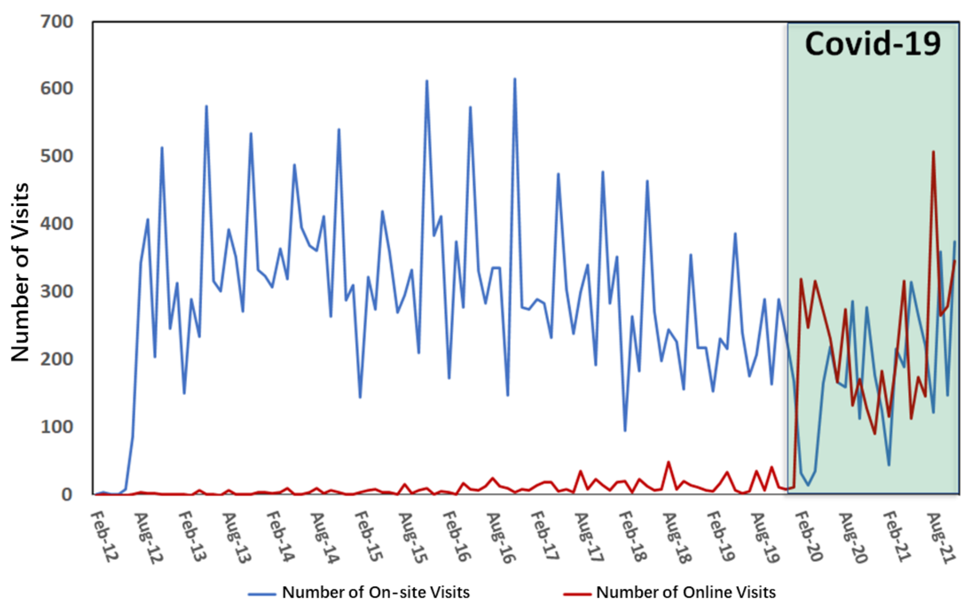


Table 1. Sample Description

Panel A contains descriptive statistics of on-site investor visits by the disclosure year, including number of site visits, number of unique hosting firms, average number of visits per hosting firm, average number of institutions participated per visit, percentage of mutual fund visits out of all on-site investor visits, percentage of non-holder visits (i.e., at least one mutual fund participant visits the firm without holding stocks) out of all mutual fund visits, and percentage of hosting firms out of all SZSE listed firms. On-site investor visit is defined as at least one investor from the fund firms visits the firm. Mutual fund visits is defined as site visits that have at least one mutual fund investor. Mutual fund holding information is from the latest available semiannual and annual reports of mutual fund before the visits. The sample for the analysis in Panel A consists of 27,931 on-site investor visits with disclosure date from July 2012 to December 2019. Panel B reports Fama-MacBeth regression results on the determinants of on-site investor visits. *LNVISIT* is log one plus number of on-site investor visits for firm in the past three months. *SIZE* is the log of circulation market cap in million CNY. *TURN* is average trading volume in past 12-month scaled by circulation shares outstanding. *MOMEN* is cumulative returns in past 12 months. *ROA* is operating income scaled by average total asset. All variables are winsorized within each cross-section at 1% and 99% levels. Cross-sectional regressions are run every calendar month. The t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for the analysis in Panel B consists of 108,874 firm-month observations spanning July 2012 to December 2019.

Panel A: Descriptive Statistics by Year

Disclosure time	# of investor visits	# of hosting firms	Average # of Visits per hosting firm	Average # of institutions per visit	% of mutual fund visits	% of non-holder visits out of all mutual fund visits	% of SZSE listed firms
2012 (from July)	1,692	539	3.14	6.50	93.4%	81.3%	36.7%
2013	3,951	871	4.54	7.23	93.4%	77.7%	57.6%
2014	4,426	1,042	4.25	8.34	93.1%	80.4%	68.5%
2015	3,956	1,064	3.72	10.18	91.9%	83.0%	66.4%
2016	4,225	1,141	3.70	11.33	89.6%	78.1%	65.8%
2017	3,799	1,044	3.64	12.85	88.6%	73.4%	56.3%
2018	3,091	874	3.54	14.40	88.3%	70.9%	42.1%
2019	2,791	811	3.44	15.63	88.6%	74.0%	38.2%
Average	3,491	923	3.75	13.25	90.9%	77.4%	53.9%

Panel B: Determinants of On-site Investor Visits

	1 *LNVISIT*	2 *LNVISIT*	3 *LNVISIT*	4 *LNVISIT*
SIZE	0.127***	0.144***	0.120***	0.104***
	(28.29)	(33.24)	(33.89)	(28.71)
TURN		0.099***	0.048***	0.038***
		(7.75)	(4.67)	(4.01)
MOMEN			0.178***	0.176***
			(12.64)	(13.33)
ROA				0.753***
				(25.52)
Intercept	-0.772***	-0.955***	-0.726***	-0.638***
	(-18.20)	(-25.30)	(-23.79)	(-21.08)
N	108,874	108,874	108,874	108,874
Adj. Avg. R^2	0.060	0.068	0.083	0.097

Table 2. Abnormal Investor Visits Strategy

Panel A reports calendar-time portfolio returns based on abnormal investor visits (*AIV*). *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past three months regressed on the log of firms' circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). Raw is monthly raw returns, market-adjusted returns is raw returns minus sample average returns, and DGTW-adjusted returns is calculated following Daniel et al. (1997). To construct this table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month based on *AIV*. All stocks are equally (value) weighted within a given portfolio, and portfolios are rebalanced every calendar month to maintain equal (value) weights. The t-statistics are reported in parentheses. Panel B reports equal- and value- weighted portfolio alphas adjusted by Fama-French Five-Factor Model based on *AIV*. Returns are measured in month m+1, where *AIV* is calculated and assigned to quintiles in month m. Alpha is the intercept from the time series regression of raw returns minus the risk-free rate, regressed on the five-factor returns. Fama French factor returns are from CSMAR. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 through December 2019.

Panel A: One-Way Sorting Portfolios

	Equal-Weighted Returns (%)			Value-Weighted Returns (%)		
	Raw	*Market-adjusted*	*DGTW-adjusted*	*Raw*	*Market-adjusted*	*DGTW-adjusted*
1 (Low AIV)	0.84	-0.72	-0.29	0.78	-0.36	-0.17
	(0.92)	(-4.10)	(-4.38)	(0.94)	(-2.89)	(-2.44)
2	1.28	-0.28	-0.15	0.96	-0.18	-0.15
	(1.24)	(-2.64)	(-2.40)	(0.97)	(-0.92)	(-1.84)
3	1.84	0.28	-0.05	1.43	0.29	-0.08
	(1.73)	(1.79)	(-0.75)	(1.39)	(1.10)	(-0.90)
4	1.85	0.29	0.13	1.46	0.32	0.15
	(1.80)	(2.12)	(1.74)	(1.63)	(1.97)	(1.33)
5 (High AIV)	1.99	0.42	0.37	1.43	0.29	0.23
	(1.92)	(3.10)	(3.64)	(1.59)	(1.83)	(2.16)
High-Low	1.14	1.14	0.66	0.65	0.65	0.39
	(5.52)	(5.52)	(4.92)	(2.92)	(2.92)	(2.64)

Panel B: Factor Model Adjusted Portfolios

Equal-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low AIV)	-0.50	0.96	0.57	-0.10	-0.28	-0.47
	(-2.63)	(32.69)	(6.82)	(-1.07)	(-2.06)	(-3.78)
2	-0.33	1.02	0.80	-0.07	-0.31	-0.22
	(-2.04)	(41.55)	(11.60)	(-0.85)	(-2.77)	(-2.06)
3	0.20	1.00	0.92	-0.23	-0.10	0.11
	(1.37)	(44.23)	(14.38)	(-3.10)	(-0.96)	(1.19)
4	0.39	0.93	0.78	-0.30	-0.24	-0.23
	(2.08)	(32.72)	(9.70)	(-3.18)	(-1.81)	(-1.86)
5 (High AIV)	0.52	0.96	0.79	-0.27	-0.18	-0.49
	(2.52)	(30.63)	(8.93)	(-2.61)	(-1.27)	(-3.63)
High-Low	1.02	0.00	0.23	-0.17	0.09	-0.01
	(7.86)	(0.17)	(4.04)	(-2.55)	(1.03)	(-0.17)
Value-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low AIV)	-0.33	0.96	0.29	-0.18	-0.23	-0.45
	(-1.91)	(35.96)	(3.84)	(-2.04)	(-1.88)	(-3.96)
2	-0.48	1.03	0.55	-0.11	-0.41	-0.23
	(-2.59)	(35.94)	(6.79)	(-1.21)	(-3.14)	(-1.83)
3	-0.07	1.02	0.72	-0.33	-0.09	0.22
	(-0.39)	(38.75)	(9.62)	(-3.75)	(-0.75)	(1.92)
4	0.34	0.93	0.37	-0.37	-0.23	-0.39
	(1.54)	(27.47)	(3.86)	(-3.33)	(-1.51)	(-2.66)
5 (High AIV)	0.38	0.92	0.37	-0.52	-0.08	-0.39
	(1.62)	(25.78)	(3.64)	(-4.41)	(-0.46)	(-2.55)
High-Low	0.71	-0.04	0.08	-0.34	0.15	0.06
	(3.84)	(-1.37)	(0.97)	(-3.63)	(1.19)	(0.52)

Table 3. Cross-Sectional Return Forecasting Regressions

This table reports predictive regressions of future stock returns. *LNVISIT* is the log of number of on-site investor visits for firm in the past three months plus one. *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). *ATOT* is the residual value from a monthly regression of log one plus number of analyst coverage for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), and cumulative returns in past 12 months (*MOMEN*), following Lee and So (2017). *SIZE* is the log of circulation market cap in million CNY. *BTM* is book-to-market ratio. *MOM12* is 12-month momentum except for the previous one month. *MOM1* is one-month momentum. *ROEQ* is quarterly operating income scaled by average total net asset. *AG* is year-over-year growth rate of total asset. *TURN1* is trading volume in last one-month scaled by circulation shares outstanding. *AVGSAR* is average of cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for the site visits that happened in past three months, following Cheng et al. (2019). *HOLDPCT* is percentage of shares held by mutual funds based on latest available semiannual or annual mutual fund reports. Δ*HOLDPCT(LAG)* equals the changes in mutual fund holding percentage based on the two latest available semiannual or annual reports prior to the portfolio formation date. Δ*HOLDPCT(FUT)* equals the change in mutual fund holding percentage from the last semiannual period to the current semiannual period. *AIV_NOFUND* is abnormal investor visits based on visit sample in which no visitor is from fund firms. All explanatory variables are standardized as zero mean and one standard deviation within each cross-section. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation. The t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

	1 RET_{m+1}	2 RET_{m+1}	3 RET_{m+1}	4 RET_{m+1}	5 RET_{m+1}	6 RET_{m+1}	7 RET_{m+1}	8 RET_{m+1}
LNVISIT	0.142							
	(1.23)							
AIV		0.264***	0.184***	0.184***	0.181***	0.181***	0.136***	0.176***
		(4.50)	(4.16)	(4.23)	(4.08)	(4.12)	(3.15)	(3.77)
ATOT			0.209**	0.211**	0.214**	0.221**	0.066	0.218**
			(2.17)	(2.19)	(2.36)	(2.39)	(0.77)	(2.34)
SIZE			-0.865***	-0.865***	-0.871***	-0.853***	-0.918***	-0.853***
			(-3.14)	(-3.14)	(-3.08)	(-3.07)	(-3.49)	(-3.06)
BTM			0.090	0.090	0.090	0.087	0.126	0.084
			(0.78)	(0.78)	(0.87)	(0.84)	(1.26)	(0.81)
MOM12			0.142	0.141	0.143	0.130	-0.102	0.128
			(1.11)	(1.11)	(1.14)	(1.03)	(-1.00)	(1.02)
MOM1			-0.491**	-0.493**	-0.493**	-0.499**	-0.676***	-0.499**
			(-2.55)	(-2.58)	(-2.60)	(-2.61)	(-3.35)	(-2.62)
ROEQ			0.240***	0.239***	0.239***	0.243***	0.268***	0.242***
			(3.27)	(3.26)	(3.30)	(3.39)	(4.11)	(3.34)
AG			-0.129***	-0.130***	-0.129***	-0.132***	-0.137***	-0.133***
			(-3.36)	(-3.39)	(-3.39)	(-3.52)	(-3.75)	(-3.56)
TURN1			-0.748***	-0.751***	-0.757***	-0.758***	-0.648***	-0.758***
			(-9.86)	(-9.96)	(-10.16)	(-10.29)	(-8.37)	(-10.29)
AVGSAR				0.007	0.013	0.012	-0.029	0.012
				(0.21)	(0.43)	(0.38)	(-0.86)	(0.38)
HOLDPCT					-0.003	-0.044	0.528***	-0.044
					(-0.03)	(-0.52)	(4.56)	(-0.52)
Δ*HOLDPCT(LAG)*						0.088***	0.116**	0.089***
						(2.65)	(2.57)	(2.71)
Δ*HOLDPCT(FUT)*							1.058***	
							(7.95)	
AIV_NOFUND								0.019
								(0.53)
Intercept	1.561	1.561	1.561	1.561	1.561	1.561	1.561	1.561
	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)
N	108,874	108,874	108,874	108,874	108,874	108,874	108,874	108,874
Avg. R^2	0.007	0.004	0.098	0.099	0.103	0.104	0.119	0.105

Table 4. Changes in Abnormal Investor Visits

Panel A reports transition matrix that shows how many firms in the highest quintile of abnormal on-site investor visits in quarter q remain in the highest quintile in q+1. Portfolios are constructed at the end of each month and monthly average values are reported. Panel B reports equal-weighted DGTW-adjusted portfolio returns based on abnormal on-site investor visits (*AIV*) and change in abnormal on-site investor visits (Δ*AIV*). All stocks are equally weighted within a given portfolio (5×3), and the portfolios are rebalanced every calendar month to maintain equal weights. The t-statistics are reported in parentheses. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

Panel A: Transition Matrix of Abnormal Investor Visits

		Quarter q+1				
		1 (Low AIV)	2	3	4	5 (High AIV)
Quarter q	1 (Low AIV)	55.8%	15.1%	2.9%	12.5%	13.7%
	2	13.3%	46.0%	20.2%	8.5%	12.0%
	3	2.9%	17.9%	49.9%	19.1%	10.3%
	4	12.9%	8.8%	16.9%	43.3%	18.0%
	5 (High AIV)	14.7%	12.2%	10.5%	17.3%	45.4%

Panel B: Conditioning on Changes (Δ*AIV*)

	Quintile portfolios based on *AIV*					
	1 (Low AIV)	2	3	4	5 (High AIV)	High-Low
Unconditional:	-0.29	-0.15	-0.05	0.13	0.37	0.66
	(-4.38)	(-2.40)	(-0.75)	(1.74)	(3.64)	(4.92)
Low Δ*AIV*	-0.37	-0.32	0.06	-0.03	0.14	0.51
	(-4.12)	(-2.68)	(0.32)	(-0.21)	(0.72)	(2.56)
Mid Δ*AIV*	-0.25	0.02	0.01	0.05	-0.01	0.24
	(-1.77)	(0.17)	(0.10)	(0.38)	(-0.05)	(0.83)
High Δ*AIV*	-0.17	-0.26	-0.07	0.19	0.41	0.60
	(-0.61)	(-1.18)	(-0.37)	(1.44)	(3.84)	(1.84)
High-Low	0.18	0.06	-0.13	0.22	0.27	
	(0.61)	(0.23)	(-0.48)	(1.05)	(1.42)	
Congruent Strategy						0.78
						(5.58)
N	1 (Low AIV)	2	3	4	5 (High AIV)	
Low Δ*AIV*	122	85	57	53	42	
Mid Δ*AIV*	65	96	113	65	22	
High Δ*AIV*	29	34	47	98	152	

Table 5. Variations in Abnormal Investor Visits

Panel A reports predictive regressions of future stock returns using different versions of abnormal on-site investor visits. *Default* is the raw measure of abnormal on-site investor visits. *Non-holder* = 1 is for on-site investor visits that at least one visitor is from mutual funds and meanwhile the hosting firm's stock is not held by the mutual fund visitor(s) before the visit, and *Non-holder* = 0 is based on on-site investor visits that at least one visitor is from mutual funds and meanwhile the hosting firm's stock is held by at least one mutual fund visitor before the visit. *Initial* = 1 is for on-site investor visits that no visitor has visited the firm in the past six months, and *Initial* = 0 is for on-site investor visits that at least one visitor has visited the same firm in the past six months. *HighCost* = 1 is for on-site investor visits that the travel cost is higher than the median of all visits for other firms in month m. *HighCost* = 0 is for on-site investor visits that the travel cost is below or equal to the median of all visits for other firms in month m. *Diff* is the average difference in monthly regression coefficients for different abnormal on-site investor visits measures. All other explanatory variables are the same as column 6 of Table 3. Mutual fund holding information is from the latest available semiannual and annual reports of mutual fund before the visits. Panel B reports the results of a series of cross-sectional analyses to evaluate the sensitivity of abnormal investor visits to various firm's characteristics. *NoCoverage* is a dummy indicator that equals to one if there are no analyst coverage for the firm in the past three months, and zero otherwise. *LowHoldPct* is a dummy indicator that equals to one if the percentage of shares held by mutual funds is below the median in the cross-section, and zero otherwise. *Loss* is a dummy indicator that equals to one if the firm's net income is negative in the previous annual report, and zero otherwise. *SmallSize* is a dummy indicator that equals to one if the firm's circulation market cap is below cross-sectional median, and zero otherwise. *Revision* is a dummy indicator coded as one if there is at least one analyst revising earnings forecasts for a visited firm in 30 days after site visit disclosure date, and zero otherwise. *Attention* is coded as one if there is news articles coverage or analyst forecast revision for a visited firm in 30 days after site visit disclosure date, and zero otherwise. Control variables include variables in column 6 of Table 3 (main text) plus interaction dummy. Time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation.The t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample consists of 108,874 firm-month observations spanning July 2012 to December 2019.

Panel A: Variations in Visit Characteristics

	AIV		*Diff*	
	Coefficient	t-*stat*	*Coefficient*	t-*stat*
Default	0.181***	(4.12)		
Non-holder = 1	0.152***	(4.78)	0.079*	(1.72)
Non-holder = 0	0.073*	(1.65)		
Initial = 1	0.170***	(3.13)	0.101*	(1.95)
Initial = 0	0.069*	(1.84)		
HighCost = 1	0.375***	(5.66)	0.108**	(2.44)
HighCost = 0	0.267***	(4.28)		

Panel B: Variations in Firm Characteristics and Investor Attention

	1	2	3	4	5	6	7
	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}
AIV	0.181***	0.088**	0.076**	0.164***	0.113***	0.186***	0.195***
	(4.12)	(2.07)	(2.13)	(3.84)	(3.13)	(4.73)	(4.71)
AIV × *NoCoverage*		0.599***					
		(7.24)					
AIV× *LowHoldPct*			0.383***				
			(3.64)				
AIV× *Loss*				0.578**			
				(2.30)			
AIV× *SmallSize*					0.210**		
					(2.50)		
AIV× *Revision*						-2.009*	
						(-1.76)	
AIV× *Attention*							-0.889*
							(-1.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	108,874	108,874	108,874	108,874	108,874	108,874	108,874
Avg. R^2	0.104	0.107	0.107	0.107	0.106	0.105	0.106

Table 6. Investor Visits and Trading Volume

This table reports equal-weighted *DGTW*-adjusted portfolio returns based on two-way sorting: abnormal investor visits (AIV) and the other indicator. At the beginning of every calendar month, firms are independently assigned into quintile portfolios based on abnormal investor visits and tercile portfolios based on the other indicator. Indicators include three-month abnormal turnover ($ABTURN3$), defined as the difference between three-month and 12-month average monthly turnover, and absolute value of three-month momentum ($AMOM3$). All stocks are equally weighted within a given portfolio (5×3), and the portfolios are rebalanced every calendar month to maintain equal weights. The t-statistics are reported in parentheses. The sample for this analysis consists of 108,874 firm-month observations spanning October 2012 to December 2019.

Panel A: Two-Way Sorting Portfolios (*AIV* and *ABTURN3*)

	Quintile portfolios based on *AIV*					
	1 (Low *AIV*)	2	3	4	5(High *AIV*)	High-Low
Unconditional:	-0.29 (-4.38)	-0.15 (-2.40)	-0.05 (-0.75)	0.13 (1.74)	0.37 (3.64)	0.66 (4.92)
Low *ABTURN3*	–0.03 (-0.17)	0.02 (0.17)	0.00 (-0.01)	0.41 (3.11)	0.59 (3.78)	0.62 (2.94)
Mid *ABTURN3*	–0.03 (-0.20)	0.10 (0.85)	0.18 (1.28)	0.23 (1.61)	0.67 (4.84)	0.70 (4.18)
High *ABTURN3*	-0.90 (-5.67)	-0.62 (-4.10)	-0.40 (-2.41)	-0.24 (-1.62)	-0.04 (-0.22)	0.86 (4.14)
High-Low	-0.87 (-3.36)	-0.64 (-2.74)	-0.39 (-1.79)	-0.65 (-3.13)	-0.63 (-3.16)	
Congruent Strategy						1.49 (5.92)
N	1 (Low *AIV*)	2	3	4	5(High *AIV*)	
Low *ABTURN3*	74	83	93	94	73	
Mid *ABTURN3*	88	88	83	73	85	
High *ABTURN3*	88	79	75	83	92	

Panel B: Two-Way Sorting Portfolios (*AIV* and *AMOM3*)

	Quintile portfolios based on *AIV*					
	1 (Low *AIV*)	2	3	4	5(High *AIV*)	High-Low
Unconditional:	-0.29 (-4.38)	-0.15 (-2.40)	-0.05 (-0.75)	0.13 (1.74)	0.37 (3.64)	0.66 (4.92)
Low *AMOM3*	-0.27 (-1.74)	-0.20 (-1.22)	-0.22 (-1.31)	0.14 (0.89)	0.50 (3.45)	0.77 (4.44)
Mid *AMOM3*	-0.16 (-1.31)	-0.03 (-0.28)	0.03 (0.29)	0.18 (1.62)	0.64 (4.92)	0.80 (4.05)
High *AMOM3*	-0.39 (-2.31)	-0.30 (-1.88)	-0.18 (-0.90)	0.04 (0.22)	0.07 (0.31)	0.46 (2.29)
High-Low	-0.12 (-0.43)	-0.10 (-0.36)	0.04 (0.15)	-0.10 (-0.33)	-0.43 (-1.51)	
Congruent Strategy						0.89 (3.34)
N	1 (Low *AIV*)	2	3	4	5(High *AIV*)	
Low *AMOM3*	85	86	84	82	80	
Mid *AMOM3*	75	87	93	83	80	
High *AMOM3*	90	78	74	85	90	

Table 7. Prediction of Future Fundamentals

Panel A reports cross-sectional regressions of future fundamental attributes. Standardized unexpected earnings (*SUE*) is defined as quarterly unexpected earnings (year-over-year change in quarterly operating income) scaled by the standard deviation of unexpected earnings over the eight preceding quarters. Size-adjusted returns (*SAR*) is defined as stock return minus corresponding size buckets' average return in one-day window centered on quarterly earnings announcement, and is further multiplied by 100. Forecast error (*FE*) is defined as actual EPS minus consensus forecast divided by total assets per share, where consensus forecast is calculated at the end of fiscal year, and *FE* is further multiplied by 100. Analyst forecast revision (*REV*) is the difference between the latest consensus forecast and the consensus forecast measured at the end of fiscal year, divided by total assets per share, and further multiplied by 100. Abnormal on-site investor visits (*AIV*) is measured at the end of corresponding fiscal period. Other control variables include abnormal analyst coverage (*ATOT*), following Lee and So (2017), average cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for all on-site investor visits in past three months (*AVGSAR*), following Cheng et al. (2019), firm's circulation market cap (*SIZE*), book-to-market ratio (*BTM*), and standardized unexpected earnings in prior four fiscal quarters (*SUE_LAG1* to *SUE_LAG4*). All variables except *SAR* are winsorized within each cross-section at 1% and 99% levels. Cross-sectional regressions are run in each period, and the time-series standard errors are Newey-West adjusted (4 lags) for heteroskedasticity and autocorrelation. The t-statistics are reported below the coefficient estimates. Sample period is from 2012 Q3 to 2019 Q3 for the analysis of *SUE* and *SAR*, and is from 2012 through 2018 for the analysis of *FE* and *REV*. Panel B shows abnormal returns around subsequent earnings announcement windows in next 6 months. *1-Day* is hedge portfolio returns (i.e., buy stocks in the top quintile of *AIV*, and sell stocks in the bottom quintile of *AIV*) in one-day window centered on earnings announcement. *3-Day* is hedge portfolio returns in three-day window centered on earnings announcement. *Pct* is the proportion of hedge portfolio returns in next 6 months that realized around earnings announcement window. The t-statistics are Newey-West adjusted for 6 lags. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for the analysis of Panel B consists of 108,874 firm-month observations spanning July 2012 to December 2019.

Panel A: Cross-Sectional Fundamental Forecasting Regressions

	1 *SUE*	2 *SUE*	3 *SAR*	4 *SAR*	5 *FE*	6 *FE*	7 *REV*	8 *REV*
AIV	0.215***	0.071***	0.113***	0.119***	0.827***	0.275***	0.051***	0.036***
	(12.92)	(4.52)	(3.86)	(3.72)	(7.38)	(5.17)	(3.75)	(3.31)
ATOT		0.093***		-0.015		0.714***		-0.006
		(8.14)		(-0.47)		(17.08)		(-0.35)
AVGSAR		1.303**		0.664		-2.258		1.405
		(2.37)		(0.45)		(-1.05)		(1.62)
SIZE		0.090***		0.051		0.688***		-0.021*
		(9.11)		(1.51)		(2.81)		(-1.80)
BTM		-0.119**		0.068		2.278***		0.393***
		(-2.37)		(0.88)		(6.42)		(7.22)
SUE_LAG1		0.364***		0.011		0.689***		0.097***
		(23.40)		(0.51)		(4.16)		(21.40)
SUE_LAG2		0.177***		-0.026		0.372**		0.044***
		(17.96)		(-1.41)		(3.43)		(5.00)
SUE_LAG3		0.112***		-0.031**		-0.022		-0.034***
		(11.66)		(-2.05)		(-0.33)		(-6.32)
SUE_LAG4		-0.187***		0.010		0.013		-0.009
		(-19.75)		(0.53)		(0.44)		(-1.40)
Intercept	0.221***	-0.585***	-0.095***	-0.533*	-2.077***	-9.147**	-0.270***	-0.271**
	(3.81)	(-7.30)	(-4.46)	(-1.89)	(-5.06)	(-3.37)	(-11.31)	(-2.12)
N	29,471	29,471	29,471	29,471	6,015	6,015	6,015	6,015
Avg. R^2	0.007	0.278	0.001	0.014	0.011	0.160	0.002	0.040

Panel B: Abnormal Returns Around Earnings Announcement Windows in Next 6 Months

	Raw Returns (%)				*Size-Adjusted Returns (%)*			
	1-Day	*Pct*	*3-Day*	*Pct*	*1-Day*	*Pct*	*3-Day*	*Pct*
Next earnings announcement window	0.15***	2.9%	0.30***	6.0%	0.09**	3.2%	0.21***	7.1%
	(4.04)		(4.36)		(2.29)		(3.11)	
All earnings announcement windows in next 6 months	0.19**	3.7%	0.45***	8.9%	0.09	3.1%	0.25*	8.3%
	(2.53)		(3.20)		(1.21)		(1.67)	

Table 8. Abnormal Investor Visits and Fund's Portfolio Management Behavior

Panel A reports predictive regressions of mutual fund holding changes around site visits. Δ*HOLDPCT(FUT)* equals the change in mutual fund holding percentage from the last semiannual period to the current semiannual period. Other variables have been defined in Table 3 and transformed from monthly frequency to semiannual frequency (e.g., *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past six months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*)). The controls include double fixed effects at the stock and semiannual levels. Standard errors are double-clustered at the stock and semiannual levels. Panel B reports predictive regressions of future stock holding ratio of mutual funds that conduct at least one visit and mutual funds that do not conduct visits to the focal firm in the past six months. Δ*HOLDPCT(FUT)*, *AIV*, and other controls have been defined in Panel A. The controls include double fixed effects at the stock and semiannual levels. Standard errors are double-clustered at the stock and semiannual levels. Nonnegative (Other) variables are winsorized at 0% (1%) and 99% levels and standardized as zero mean and one standard deviation. The t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The sample covers the period January 2013 to December 2019.

Panel A: *AIV* and Change of Mutual Fund Holding Ratio

	1 Δ*HOLDPCT(FUT)*	2 Δ*HOLDPCT(FUT)*	3 Δ*HOLDPCT(FUT)*	4 Δ*HOLDPCT(FUT)*
AIV	0.084***	0.122***	0.096***	0.095***
	(5.95)	(8.56)	(7.94)	(7.97)
HOLDPCT(LAG)		-0.634***	-0.754***	-0.779***
		(-13.45)	(-16.72)	(-15.28)
ATOT			0.169***	0.172***
			(15.60)	(16.09)
SIZE			0.245***	0.256***
			(8.14)	(8.27)
BTM			-0.099***	-0.104***
			(-4.17)	(-4.22)
MOM12			0.232***	0.220***
			(8.90)	(8.17)
MOM1			0.146***	0.143***
			(7.13)	(7.01)
ROE			-0.050***	-0.048***
			(-5.50)	(-5.19)
AG			-0.012	-0.010
			(-1.61)	(-1.28)
TURN1			-0.146***	-0.142***
			(-11.26)	(-11.98)
AVGSAR			0.000	0.000
			(0.04)	(0.01)
Δ*HOLDPCT(LAG)*				0.042**
				(2.50)
Stock FEs	Yes	Yes	Yes	Yes
Semiannual FEs	Yes	Yes	Yes	Yes
N	26,255	23,048	22,939	22,939
Adjusted R^2	-0.032	0.173	0.275	0.276

Panel B: Visiting VS. Non-visiting Funds

	Held by funds with at least one visit		Held by funds without visits	
	1 Δ*HOLDPCT(FUT)*	2 Δ*HOLDPCT(FUT)*	3 Δ*HOLDPCT(FUT)*	4 Δ*HOLDPCT(FUT)*
AIV	0.332***	0.260***	-0.049***	-0.067***
	(15.54)	(14.06)	(-3.28)	(-4.65)
Stock FEs	Yes	Yes	Yes	Yes
Semiannual FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	8,385	5,784	23,413	20,012
Adjusted R^2	-0.092	0.537	-0.054	0.362

Table 9. On-site Investor Visits and Fund's Performance

Panel A reports estimates from Fama and MacBeth (1973) regressions of future fund performance on the most recent month's on-site investor visits of mutual fund firms and fund characteristics. α^{4F}_{m+1} is the fund's future one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations estimated using the preceding 24 monthly fund returns. *LNVISIT_FUND* is the log of one plus number of on-site investor visits from mutual fund firm in the past one month. Following Bai et al. (2022), the fund characteristics include the cumulative returns of mutual fund over the prior twelve months (*RET*), the return volatility of mutual fund measured as the standard deviation of monthly fund return over the prior twelve months (*VOL*), the prior twelve-month normalized net flow into mutual fund and defined as $(TNA_t - TNA_{t-12}(1 + R_{t,t-11}))/TNA_{t-12}$ (*FLOW*), the log of mutual fund's total net asset (*TNA*) at the latest available quarter (*SIZE*), the log of mutual fund's age since inception (*AGE*), the sum of management fee rate and custodian fee rate (*EXPENSE*). Newey and West (1987) t–statistics with a lag of 6 are reported in parentheses. The sample covers the period July 2012 to December 2019. Panel B estimates the impact of travel restrictions on funds that rely heavily on site-visits by pooled regressions. *postFeb2020* is an indicator variable that equals one starting in February 2020, *SiteVisit_Intensity* is measured as the log of one plus the average number of site-visiting for specific fund firm in the pre-COVID era (i.e., from January 2015 to January 2020), and *SiteVisit_Intensity* × *postFeb2020* is an interaction term between the two variables. The other controls are defined in Panel A. Standard errors are clustered at month levels and t–statistics are reported in parentheses. The sample covers the period 2015 to 2021. Except for *postFeb2020*, *SiteVisit_Intensity* and *SiteVisit_Intensity* × *postFeb2020*, all variables are winsorized within each cross-section at 1% and 99% levels and standardized as zero mean and one standard deviation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: On-site Investor Visits and Fund Alpha

	1 α^{4F}_{m+1}	2 α^{4F}_{m+1}	3 α^{4F}_{m+1}	4 α^{4F}_{m+1}	5 α^{4F}_{m+1}	6 α^{4F}_{m+1}	7 α^{4F}_{m+1}
LNVISIT_FUND	0.067***	0.061***	0.056***	0.056***	0.057***	0.053***	0.053***
	(4.01)	(3.67)	(3.32)	(3.31)	(3.42)	(3.00)	(3.16)
RET		0.090**	0.119**	0.123**	0.122**	0.118**	0.118**
		(2.00)	(2.48)	(2.54)	(2.52)	(2.45)	(2.44)
VOL			-0.059	-0.057	-0.055	-0.054	-0.060
			(-0.89)	(-0.87)	(-0.83)	(-0.83)	(-0.92)
FLOW				-0.003	-0.003	-0.012	-0.010
				(-0.18)	(-0.18)	(-0.71)	(-0.60)
SIZE					-0.010	0.018	0.019
					(-0.56)	(0.69)	(0.73)
AGE						-0.064*	-0.069*
						(-1.72)	(-1.87)
EXPENSE							0.039
							(1.63)
N	99,488	99,488	99,488	99,378	99,378	99,376	99,376
Avg. R^2	0.006	0.035	0.076	0.079	0.084	0.088	0.095

Panel B: Travel restrictions, On-site Visits, and Fund Performance

	1 α^{4F}_{m+1}	2 α^{4F}_{m+1}	3 α^{4F}_{m+1}	4 α^{4F}_{m+1}
SiteVisit_Intensity	0.069**	0.070**	0.079***	0.083***
	(2.59)	(2.63)	(2.91)	(3.20)
postFeb2020	0.249	0.252	0.250	0.251
	(1.06)	(1.07)	(1.06)	(1.07)
SiteVisit_Intensity × *postFeb2020*	-0.093**	-0.094**	-0.093**	-0.093**
	(-2.18)	(-2.17)	(-2.17)	(-2.18)
RET	0.211***	0.210***	0.212***	0.210***
	(3.56)	(3.55)	(3.53)	(3.50)
VOL	-0.053	-0.053	-0.051	-0.048
	(-0.96)	(-0.96)	(-0.90)	(-0.76)
FLOW		0.005	0.007	0.006
		(0.38)	(0.53)	(0.41)
SIZE			-0.022	-0.016
			(-0.94)	(-0.67)
AGE				-0.033
				(-1.11)
EXPENSE				0.006
				(0.20)
N	143,872	143,713	143,713	143,689
Adjusted R^2	0.006	0.006	0.006	0.006

Internet Appendix for

Investor Corporate Visits and Predictable Returns

July 22, 2024

In this Internet Appendix, we provide additional robustness tests. First, we rule out the information risk explanation of *AIV* return predictability (Table A1). We report the negative correlation between *AIV* and information risk, and document the robustness of the return predictability after controlling information risk. These results show that our documented return predictability of *AIV* is unlikely to be explained by information risk.

Second, as *AIV* may be correlated with other unknown firm traits, we include lagged *LNVISIT* to the *AIV* determinant model, i.e., Eq. (1) in the main text, to control for persistent firm characteristics. Using this new determinant model, we find that although the magnitude of average monthly alphas is lower than the determinant model used in the main text, they are still statistically and economically significant (Table A2). Fama-MacBeth regressions results show that *AIV* is statistically significant in all six specifications (Table A3).

Third, following Cohn, Liu and Wardlaw (2022), we report the robustness of return predictability using the *VISIT* raw values (instead of the log(1+Y) specification) in cross-sectional Poisson regression to calculate *AIV* (Table A4 and Table A5). We show that from both perspectives of regression and portfolio sort, *AIV* using the raw values can forecast future stock returns.

Fourth, we document the robustness of our main results when *AIV* is calculated based on the total number of visiting investors (instead of the number of on-site visits) for firm *i* in the past three months (Table A6 and Table A7). Our main results using this new model are consistent with the main text.

Fifth, we summarize the institutional differences between the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), especially on disclosure regulations (Table A8), to help readers better understand the differences between the two major exchanges in China.

1. Excluding information risk explanation

One risk-based alternative explanation of our findings is that investors endogenously choose to visit firms with opaque information environment, thus *AIV* can be viewed as a proxy for information risk and is positively relative to the expected return. To alleviate this concern, we conduct the two tests below to show that the *AIV* return predictability is not due to information risk.[1] Table A1 reports the results.

First, we examine the correlation between *AIV* and measures of information risk. We use volume synchronized possibility of informed trading (*VPIN*) and time-weighted bid-ask spread (*SPREAD*) to measure information risk (Easley et al., 2012; McInish and Wood, 1992). Following Easley et al. (2012), we calculate *VPIN* as:

$$VPIN = \frac{\sum_{\tau=1}^{n} \left| V_{\tau}^{S} - V_{\tau}^{B} \right|}{nV},$$

where V is the trading volume in every bucket, V_{τ}^{S} and V_{τ}^{B} are sell and buy volumes identified based on one-minute time bars, and n (n = 8) is the number of buckets used to approximate the expected trade imbalance.

Following McInish and Wood (1992), we calculate *SPREAD* as:

$$SPREAD = \sum_{i=1}^{N} \frac{\left(t_{i+1} - t_i\right)}{\left(T' - t_1\right)} BAS_i,$$

where *BAS* is computed for every quotation as: $BAS = \left[\left(ask - bid\right) / \left(\left(ask + bid\right)/2\right)\right]$; supposed that in the interval (T, T'), there are N quotation updates, occurring at times t_i, i = 1, …, N, with spreads BAS_i, i = 1, …, N where $t_0 = T$ and $t_{N+1} = T'$.

Table A1 Panel A presents the Pearson correlations among variables: *AIV*, *VPIN*, and *SPREAD*. If the information risk hypothesis holds, we would expect to see a positive

[1] We would like to thank the referee for this suggestion.

correlation between *AIV* and other information risk proxies. Table R1 Panel A shows that both *VPIN* and *SPREAD* are significantly negatively correlated with *AIV*, which is inconsistent with potential concerns that investors tend to visit firms with higher information risk.

Additionally, Table A1 Panel B shows that the return predictability of *AIV* remains unchanged after controlling for information risk proxies. We conduct Fama-MacBeth regressions where the dependent variable is the firm's raw returns in month *m+1* (denoted RET_{m+1}) while controlling for a host of variables nominated by the previous literature (see column 6 of Table 3 of main text) and information risk, proxied by *VPIN* and *SPREAD*. The robustness of our findings across these tests further supports the idea that our findings are unlikely explained by information risk.

2. Alternative construction of *AIV*: including lagged *LNVISIT*

One concern raised by the referee is that *AIV* could still proxy for some missing firm characteristics that are correlated with future stock returns in the cross-section. For example, geographic location, the nature of the business, the effectiveness of investor relation department, etc. As *AIV* may be correlated with other unknown firm traits, we include lagged *LNVISIT* to the determinant model, i.e., Eq. (1), to control for persistent firm characteristics.[2] Specifically, we calculate abnormal site visits for firm *i* in calendar month *m* by estimating the following regressions:

$$\begin{aligned} LNVISIT_{im} = \beta + \beta_1 SIZE_{im} + \beta_2 TURN_{im} + \beta_3 MOMEN_{im} + \beta_4 ROA_{im} \\ + \beta_5 LNVISIT(LAG)_{im} + \varepsilon_{im} \end{aligned} \tag{1}$$

where *LNVISIT* is the log of one plus number of on-site investor meetings for firm *i* in the three months leading up to *m*. *SIZE* is the log of market capitalization in million CNY in

[2] We would like to thank the referee for this suggestion.

month *m*. *TURN* is average trading volume in past 12 months scaled by shares outstanding. *MOMEN* is cumulative returns in past 12 months. *ROA* is operating income scaled by total assets. *LNVISIT(LAG)* is lagged *LNVISIT.* *AIV* for each firm-month is the regression residuals (i.e., ε) from estimating Eq. (1).

Table A2 Panel A contains the coefficients from estimating Eq. (1). It shows strong autocorrelation between *LNVISIT(LAG)* and *LNVISIT*, as the coefficient of *LNVISIT(LAG)* is statistically significant.

Table A2 Panel B and C report our main results using this new determinant model. Specifically, we show that high *AIV* firms significantly outperform low *AIV* stocks for both equal- and value-weighted portfolios using raw, market-adjusted, and characteristic-adjusted returns following Daniel et al. (1997). Panel B of Table A2 shows that the equal-weighted *AIV* quintile strategy yields average monthly returns of 51 basis points (t=3.35), which equates to 6.12% on an annualized basis. Similarly, *AIV* strategy returns are 43 basis points per month (t=2.18) when value-weighted, which annualizes to 5.16% per year. Although the magnitude of average monthly alphas is lower than the determinant model used in the main text, they are still statistically and economically significant.

In Panel C of Table A2, we report the portfolio alphas as well as the factor loadings on each of the Fama and French (2015) five factors. We find that after controlling for the five factors, the t-statistics corresponding to *AIV* strategies generally increase, while yielding similar annualized returns. Further, in Table A3, we conduct Fama-MacBeth regressions where the dependent variable is the firm's raw return in month $m+1$ (denoted RET_{m+1}) while controlling for a host of variables nominated by prior literature. Consistent with the the portfolio results, we find that *AIV* is statistically significant in all six specifications.

3. Alternative construction of *AIV*: using raw *VISIT* value

According to Cohn, Liu and Wardlaw (2022), we use the *VISIT* raw values, instead of the log(1+Y) specification, in cross sectional Poisson regression to calculate *AIV*.[3] Specifically, we calculate *AIV* as the residual value from a monthly Poisson regression of raw number of investor site visits for firm in the past three months regressed on the log of firms' circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). Table A4 and A4 demonstrate from the perspectives of regression and portfolio sort that *AIV* using the raw values predicts future stock returns.

Table A4 Panel A reports Fama-MacBeth regression results on the determinants of investor site visits. The raw number of investor site visits are increasing with contemporaneously measured firm size (t = 24.41), firms' momentum (t = 13.82), and *ROA* (t = 23.81).

Table A4 Panel B shows that our main results are robust using this new model. High *AIV* firms significantly outperform low *AIV* firms for both equal- and value-weighted portfolios using raw, market-adjusted, and characteristic-adjusted returns. Panel B of Table A4 shows that the equal-weighted *AIV* quintile strategy yields average monthly returns of 111 basis points (t = 5.15), which annualizes to 13.32% per year. Similarly, *AIV* strategy returns are 64 basis points per month (t = 2.87) when value-weighted, which annualize to 7.68% per year. In Panel C of Table A4, we report the portfolio alpha as well as the factor loadings on each of the Fama and French (2015) five factors. The average monthly alpha and the t-statistics reported in Table R7 Panel B and Panel C are similar with our results in the main text.

[3] We would like to thank the referee for this suggestion.

In Table A5, we conduct Fama-MacBeth regressions where the dependent variable is the firm's raw return in month *m+1* (denoted RET_{m+1}) while controlling for a host of variables nominated by the literature. Consistent with the portfolio results, columns (2) through (7) highlight a robust positive relation between *AIV* and future returns across all six specifications.

4. Alternative construction of *AIV*: using *LNVISIT(NUM)*

In this section, we replace *LNVISIT* with *LNVISIT(NUM)*, which is log one plus number of the total number of visiting investors for firm in the past three months, the determinant model, i.e., Eq. (1).[4] Table A6 and A7 demonstrate from the perspectives of regression and portfolio sort that the *AIV* using the total number of visiting investors can predict future stock returns.

Table A6 Panel A reports Fama-MacBeth regression results on the determinants of *LNVISIT(NUM)*. Table A7 Panel B and Panel C report our main results using this new model. Specifically, we show that high *AIV* firms still significantly outperform low *AIV* stocks for both equal- and value-weighted portfolios using raw, market-adjusted, and characteristic-adjusted returns following Daniel et al. (1997). The average monthly alpha and the *t*-statistics reported in Table A6 Panel B and Panel C are similar with our results in the main text. The equal-weighted *AIV* quintile strategy yields average monthly returns of 105 basis points (*t*=4.64), which annualizes to 12.60% per year. Similarly, *AIV* strategy returns are 65 basis points per month (*t*=2.65) when value-weighted, which annualizes to 7.80% per year. After controlling for the five factors, the *t*-statistics corresponding to *AIV* strategies generally increase, while yielding similar annualized returns.

[4] We would like to thank the referee for this suggestion.

Table A7 reports the Fama-MacBeth regressions results where the dependent variable is the firm's raw return in month $m+1$ (denoted RET_{m+1}) while controlling for a host of variables nominated by the literature. Consistent with our findings in the main text, Table A7 columns (2) through (7) show a robust positive relation between *AIV* and future returns across all six specifications.

5. Institutional differences across stock exchanges

One major concern raised by the editor is that there are two major stock exchanges in China, what are the institutional background and policy implications when SZSE requires such disclosure, i.e., site-visit disclosure, while SHSE does not.

To address this question, we document a short summary of the institutional background and policy implications difference between the two major stock exchanges in China, the SHSE and the SZSE, especially with respect to disclosure regulation.

Founded in 1990, the SHSE is China's oldest and largest stock exchange. The SZSE is the second stock exchange in China. Compared with the SHSE, the SZSE has firms with lower market capitalization and tends to attract more start-up firms and firms from emerging industries. We provide more details in Table A8: Panel A shows a timeline of the development history of the two exchanges; Panel B reports a summary of the key statistics of the two exchanges; Panel C summarizes the main differences in market characteristics of the SHSE and the SZSE.

Both the SHSE and the SZSE are supervised and regulated by the China Securities Regulatory Commission (CSRC), and most of the regulations are the same on both exchanges. However, due to the different development history and characteristics, there are differences in regulatory requirements. Panel D of Appendix E1 provides a comparison of differences in disclosure requirements between the two exchanges. Specifically, the information disclosure reform for the SZSE preceded that for the SHSE and required that more information be disclosed including the disclosure of site visits. We discuss the differences in detail below.

(1) Site visit disclosure

Both the Main Board and the Growth Enterprise Market (GEM) of the SZSE require firms to disclose specific information of site visits (Cheng et al., 2016; Cheng et al., 2019; Bowen et al., 2018). The information about site visits became publicly available in 2008 when the SZSE issued a rule requiring the disclosure of site visits in listed firms' annual reports. The disclosure requirement became effective from 2009 and has been strictly enforced. In July 2012, the SZSE introduced a new requirement for listed firms to publicly disclose a standard site visit report on each private meeting within two trading days of the date on the stock exchange's web portal, Hu Dong Yi (互动易). However, there are no such requirement upon firms listed on the SHSE main board.

(2) Information disclosure reform

The SZSE released the assessment methods for information disclosure on the SZSE in 2011. Two years later, the SHSE issued the assessment methods for information disclosure on the SHSE. The information disclosure system reform of the SZSE is considered deeper than that of the SHSE (Wang et al., 2022), because the SZSE reports the results of information disclosure quality assessment within the scope of listed firms and discloses it to the public, while the SHSE only reports the results of information disclosure quality assessment within the scope of listed firms but not to the public.

(3) Internet-based communication platform

The SZSE started using an Internet-based interactive platform earlier than the SHSE. In January 2010, the SZSE launched the Hu Dong Yi platform for investors to communicate directly with listed firms. In November 2011, an upgraded version of Hu Dong Yi based on the Web 2.0 platform was launched. The SHSE platform, e Hu Dong (e 互动), was launched 3.5 years later than the SZSE, in July 2013.

(4) Social responsibility disclosure

In September 2006, the SZSE issued the first regulatory system on social responsibility disclosure on the Chinese capital market, encouraging firms to establish relevant institutional systems to disclose external CSR reports (Lin, 2010; Wang et al., 2013). Only firms listed on the SZSE were subjected to the regulatory regime of the guidance during 2006-2008. The SHSE did not have disclosure requirements for social responsibility reporting until 2008, when the SHSE and the SZSE simultaneously issued the Notice on the Work of 2008 Annual Reports of Listed Firms.

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Table A1. Abnormal Investor Visits and Information Risk

This table examines the potential information risk explanation of the abnormal investor visit strategy. Panel A presents Pearson correlations among variables: *AIV*, *VPIN*, and *SPREAD*. *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). Proxies for information risk include volume synchronized possibility of informed trading (*VPIN*) for the last month following Easley et al. (2012), and time-weighted bid-ask spread (*SPREAD*) for the last month following McInish and Wood (1992). Panel B reports the results of a series of cross-sectional analyses to evaluate the effect of abnormal investor visits to information risk. Control variables include variables in column 6 of Table 3 (main text) plus interaction dummies. Time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample of *VPIN* spans from July 2015 to December 2019, and *SPREAD* spans from January 2017 to December 2019.

Panel A: Pearson Correlations			
	AIV	*VPIN*	*SPREAD*
AIV		-0.03***	-0.06***
VPIN	-0.03***		0.20***
SPREAD	-0.06***	0.20***	

Panel B: *AIV*'s Predictability under Information Risk			
	(1)	(2)	(3)
	RET_{m+1}	RET_{m+1}	RET_{m+1}
AIV	0.181***	0.366***	0.449***
	(4.12)	(4.33)	(5.37)
VPIN		-0.086*	
		(-1.77)	
SPREAD			0.100
			(1.07)
Controls	Yes	Yes	Yes
N	108,874	71,364	53,502
Adj. R^2	0.104	0.099	0.112

Table A2. Abnormal-Investor-Visit Strategy with lagged *LNVISIT* as Site Visit Determinant

Panel A reports Fama-MacBeth regression results on the determinants of on-site investor visits. *LNVISIT* is log one plus number of on-site investor visits for firm in the past three months. *SIZE* is the log of circulation market cap in million CNY. *TURN* is average trading volume in past 12-month scaled by circulation shares outstanding. *MOMEN* is cumulative returns in past 12 months. *ROA* is operating income scaled by average total asset. *LNVISIT(LAG)* is lagged *LNVISIT*. All variables are winsorized within each cross-section at 1% and 99% levels. We run cross-sectional regressions every calendar month. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. Panel B reports calendar-time portfolio returns based on abnormal investor visits (*AIV*). *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past three months regressed on the log of firms' circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), return on total asset (*ROA*) and lagged *LNVISIT* (*LNVISIT(LAG)*). *Raw* is monthly raw returns, *Market-adjusted* returns are raw returns minus sample average returns, and *DGTW-adjusted* returns are calculated following Daniel et al. (1997). To construct this table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month based on *AIV*. All stocks are equally (value) weighted within a given portfolio, and portfolios are rebalanced every calendar month to maintain equal (value) weights. The *t*-statistics are reported in parentheses. Panel C reports equal- and value- weighted portfolio alphas adjusted by Fama-French Five-Factor Model based on *AIV*. Returns are measured in month *m+1*, where *AIV* is calculated and assigned to quintiles in month *m*. Alpha is the intercept from the time series regression of raw returns minus the risk-free rate, regressed on the five factor returns. Fama French factor returns are from CSMAR. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 through December 2019.

Panel A: Determinants of On-site Investor Visits					
	(1)	(2)	(3)	(4)	(5)
	LNVISIT	*LNVISIT*	*LNVISIT*	*LNVISIT*	*LNVISIT*
SIZE	0.127***	0.144***	0.120***	0.104***	0.063***
	(28.29)	(33.24)	(33.89)	(28.71)	(22.77)
TURN		0.099***	0.048***	0.038***	0.015*
		(7.75)	(4.67)	(4.01)	(1.88)
MOMEN			0.178***	0.176***	0.108***
			(12.64)	(13.33)	(11.91)
ROA				0.753***	0.417***
				(25.52)	(15.00)
LNVISIT(LAG)					0.416***
					(54.60)
Intercept	-0.772***	-0.955***	-0.726***	-0.638***	-0.388***
	(-18.20)	(-25.30)	(-23.79)	(-21.08)	(-16.35)
N	108,874	108,874	108,874	108,874	104,381
Adj. Avg. R^2	0.061	0.069	0.086	0.101	0.259

Panel B: One-Way Sorting Portfolios						
	Equal-Weighted Returns (%)			Value-Weighted Returns (%)		
	Raw	*Market-adjusted*	*DGTW-adjusted*	*Raw*	*Market-adjusted*	*DGTW-adjusted*
1 (Low *AIV*)	1.44	-0.13	-0.02	1.02	-0.11	-0.06
	(1.45)	(-1.04)	(-0.30)	(1.18)	(-0.86)	(-0.78)
2	0.90	-0.67	-0.35	0.61	-0.52	-0.24
	(0.91)	(-5.04)	(-4.18)	(0.66)	(-3.11)	(-2.71)
3	1.71	0.14	-0.06	1.32	0.19	-0.08
	(1.61)	(0.90)	(-0.71)	(1.30)	(0.75)	(-0.72)
4	1.87	0.30	0.11	1.35	0.23	0.07
	(1.79)	(2.32)	(1.61)	(1.48)	(1.37)	(0.77)
5 (High *AIV*)	1.94	0.37	0.33	1.45	0.32	0.25
	(1.89)	(2.8)	(3.29)	(1.6)	(2.05)	(2.35)
High-Low	0.51	0.51	0.35	0.43	0.43	0.31
	(3.35)	(3.35)	(2.90)	(2.18)	(2.18)	(2.12)

Panel C: Factor Model Adjusted Portfolios						
Equal-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.01	0.95	0.74	-0.12	-0.26	-0.57
	(-0.04)	(29.88)	(8.49)	(-1.19)	(-1.82)	(-4.33)
2	-0.53	0.99	0.61	-0.13	-0.37	-0.13
	(-3.25)	(37.96)	(8.43)	(-1.58)	(-3.11)	(-1.18)
3	0.09	0.99	0.87	-0.19	-0.17	0.06
	(0.61)	(41.62)	(13.30)	(-2.50)	(-1.58)	(0.64)
4	0.39	0.94	0.76	-0.24	-0.35	-0.31
	(2.25)	(34.16)	(10.07)	(-2.73)	(-2.83)	(-2.71)
5 (High *AIV*)	0.53	0.93	0.75	-0.31	-0.22	-0.44
	(2.55)	(28.13)	(8.230)	(-2.93)	(-1.49)	(-3.23)
High-Low	0.54	-0.02	0.00	-0.19	0.04	0.13
	(3.61)	(-0.90)	(0.07)	(-2.49)	(0.37)	(1.30)
Value-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.07	0.93	0.35	-0.22	-0.25	-0.60
	(-0.34)	(29.73)	(4.04)	(-2.26)	(-1.81)	(-4.68)
2	-0.62	1.00	0.36	-0.16	-0.34	-0.07
	(-3.43)	(34.58)	(4.47)	(-1.79)	(-2.61)	(-0.61)
3	-0.11	0.97	0.62	-0.25	-0.31	0.02
	(-0.54)	(30.87)	(7.20)	(-2.50)	(-2.16)	(0.15)
4	0.27	0.91	0.31	-0.38	-0.41	-0.38
	(1.23)	(25.78)	(3.20)	(-3.42)	(-2.60)	(-2.65)
5 (High *AIV*)	0.38	0.91	0.40	-0.50	-0.06	-0.38
	(1.67)	(25.20)	(4.03)	(-4.33)	(-0.36)	(-2.54)
High-Low	0.45	-0.02	0.05	-0.27	0.20	0.22
	(2.37)	(-0.50)	(0.66)	(-2.87)	(1.45)	(1.80)

Table A3. Cross-Sectional Return Forecasting Regressions with lagged *LNVISIT* in Eq. (1)

This table reports predictive regressions of future stock returns. *LNVISIT* is the log of number of on-site investor visits for firm in the past three months plus one. *AIV* is the residual value from a monthly regression of lagged log one plus number of on-site investor visits for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). *ATOT* is the residual value from a monthly regression of log one plus number of analyst coverage for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), and cumulative returns in past 12 months (*MOMEN*), following Lee and So (2017). *SIZE* is the log of circulation market cap in million CNY. *BTM* is book-to-market ratio. *MOM12* is 12-month momentum except for the previous one month. *MOM1* is one-month momentum. *ROEQ* is quarterly operating income scaled by average total net asset. *AG* is year-over-year growth rate of total asset. *TURN1* is trading volume in last one-month scaled by circulation shares outstanding. *AVGSAR* is average of cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for the site visits that happened in past three months, following Cheng et al (2019). *HOLDPCT* is percentage of shares held by mutual funds based on latest available semiannual or annual mutual fund reports. Δ*HOLDPCT(LAG)* equals the change in mutual fund holding percentage in latest available semiannual period. Δ*HOLDPCT(FUT)* equals the change in mutual fund holding percentage in the next semiannual period. *AIV_NOFUND* is abnormal investor visits based on visit sample in which no visitor is from fund firms. All explanatory variables are standardized as zero mean and one standard deviation within each cross-section. We run cross-sectional regressions every calendar month, and the time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}
LNVISIT	0.142						
	(1.23)						
AIV		0.194***	0.146***	0.147***	0.144***	0.145***	0.096**
		(3.55)	(3.36)	(3.44)	(3.35)	(3.41)	(2.36)
ATOT			0.241**	0.243**	0.253***	0.259***	0.098
			(2.35)	(2.38)	(2.66)	(2.67)	(1.08)
SIZE			-0.886***	-0.886***	-0.883***	-0.865***	-0.933***
			(-3.10)	(-3.11)	(-3.01)	(-2.99)	(-3.40)
BTM			0.070	0.070	0.067	0.066	0.106
			(0.55)	(0.56)	(0.59)	(0.58)	(0.96)
MOM12			0.151	0.149	0.153	0.143	-0.087
			(1.12)	(1.11)	(1.16)	(1.07)	(-0.81)
MOM1			-0.496**	-0.497**	-0.497**	-0.502**	-0.681***
			(-2.54)	(-2.57)	(-2.59)	(-2.59)	(-3.31)
ROEQ			0.239***	0.238***	0.238***	0.242***	0.267***
			(3.21)	(3.20)	(3.27)	(3.36)	(4.07)
AG			-0.141***	-0.142***	-0.142***	-0.144***	-0.148***
			(-3.39)	(-3.43)	(-3.41)	(-3.53)	(-3.63)
TURN1			-0.733***	-0.736***	-0.743***	-0.744***	-0.633***
			(-9.43)	(-9.53)	(-9.75)	(-9.91)	(-8.00)
AVGSAR				0.009	0.014	0.012	-0.031
				(0.26)	(0.44)	(0.37)	(-0.93)
HOLDPCT					-0.020	-0.061	0.527***
					(-0.25)	(-0.80)	(4.54)
ΔHOLDPCT(LAG)						0.079**	0.109**
						(2.24)	(2.35)
ΔHOLDPCT(FUT)							1.075***
							(7.58)
Intercept	1.561	1.571	1.572	1.572	1.572	1.572	1.573
	(1.60)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)	(1.56)
N	108,874	104,381	104,381	104,381	104,381	104,381	104,381
Avg. R^2	0.007	0.002	0.098	0.099	0.103	0.104	0.119

Table A4. Abnormal-Investor-Visit Strategy using Poisson Regressions to Estimate *AIV*

Panel A reports Fama-MacBeth regression results on the determinants of on-site investor visits. *LNVISIT* is log one plus number of on-site investor visits for firm in the past three months. *SIZE* is the log of circulation market cap in million CNY. *TURN* is average trading volume in past 12-month scaled by circulation shares outstanding. *MOMEN* is cumulative returns in past 12 months. *ROA* is operating income scaled by average total asset. *LNVISIT(LAG)* is lagged *LNVISIT*. All variables are winsorized within each cross-section at 1% and 99% levels. We run cross-sectional regressions every calendar month. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. Panel B reports calendar-time portfolio returns based on abnormal investor visits (*AIV*). *AIV* is the residual value from a monthly regression of log one plus number of on-site investor visits for firm in the past three months regressed on the log of firms' circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), return on total asset (*ROA*) and lagged *LNVISIT* (*LNVISIT(LAG)*). *Raw* is monthly raw returns, *Market-adjusted* returns are raw returns minus sample average returns, and *DGTW-adjusted* returns are calculated following Daniel et al. (1997). To construct this table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month based on *AIV*. All stocks are equally (value) weighted within a given portfolio, and portfolios are rebalanced every calendar month to maintain equal (value) weights. The *t*-statistics are reported in parentheses. Panel C reports equal- and value- weighted portfolio alphas adjusted by Fama-French Five-Factor Model based on *AIV*. Returns are measured in month *m+1*, where *AIV* is calculated and assigned to quintiles in month *m*. Alpha is the intercept from the time series regression of raw returns minus the risk-free rate, regressed on the five factor returns. Fama French factor returns are from CSMAR. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 through December 2019.

Panel A: Determinants of On-site Investor Visits

	(1) *VISIT*	(2) *VISIT*	(3) *VISIT*	(4) *VISIT*
SIZE	0.485***	0.523***	0.435***	0.374***
	(21.95)	(26.81)	(27.32)	(24.41)
TURN		0.242***	0.046	0.027
		(5.62)	(1.17)	(0.75)
MOMEN			0.555***	0.556***
			(12.92)	(13.82)
ROA				2.346***
				(23.81)
Intercept	-4.788***	-5.213***	-4.394***	-4.053***
	(-21.43)	(-27.02)	(-28.15)	(-26.87)
N	108,874	108,874	108,874	108,874
Adj. Avg. R^2	0.061	0.069	0.086	0.101

Panel B: One-Way Sorting Portfolios						
	Equal-Weighted Returns (%)			Value-Weighted Returns (%)		
	Raw	*Market-adjusted*	*DGTW-adjusted*	*Raw*	*Market-adjusted*	*DGTW-adjusted*
1 (Low *AIV*)	0.89	-0.68	-0.25	0.81	-0.33	-0.16
	(0.96)	(-3.68)	(-3.73)	(0.98)	(-2.53)	(-2.45)
2	1.24	-0.32	-0.20	0.99	-0.15	-0.12
	(1.21)	(-3.14)	(-3.10)	(1.01)	(-0.82)	(-1.63)
3	1.88	0.32	0.01	1.53	0.39	-0.03
	(1.76)	(2.05)	(0.08)	(1.52)	(1.58)	(-0.37)
4	1.81	0.25	0.05	1.39	0.25	0.07
	(1.76)	(1.84)	(0.64)	(1.53)	(1.34)	(0.62)
5 (High *AIV*)	2.00	0.43	0.39	1.45	0.31	0.26
	(1.92)	(3.16)	(3.82)	(1.60)	(2.01)	(2.45)
High-Low	1.11	1.11	0.65	0.64	0.64	0.41
	(5.15)	(5.15)	(4.78)	(2.87)	(2.87)	(2.80)

Panel C: Factor Model Adjusted Portfolios						
Equal-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.47	0.98	0.58	-0.11	-0.20	-0.49
	(-2.38)	(32.53)	(6.82)	(-1.13)	(-1.47)	(-3.79)
2	-0.31	1.00	0.75	-0.14	-0.31	-0.15
	(-2.08)	(43.72)	(11.62)	(-1.92)	(-2.90)	(-1.49)
3	0.22	0.99	0.93	-0.18	-0.15	0.04
	(1.44)	(41.44)	(13.68)	(-2.32)	(-1.36)	(0.39)
4	0.31	0.93	0.81	-0.26	-0.24	-0.19
	(1.76)	(34.43)	(10.52)	(-2.94)	(-1.91)	(-1.67)
5 (High *AIV*)	0.52	0.96	0.80	-0.27	-0.21	-0.50
	(2.49)	(30.08)	(8.79)	(-2.53)	(-1.42)	(-3.65)
High-Low	0.99	-0.01	0.22	-0.16	-0.01	-0.01
	(7.76)	(-0.67)	(3.94)	(-2.42)	(-0.07)	(-0.16)
Value-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.28	0.98	0.28	-0.23	-0.13	-0.44
	(-1.56)	(35.77)	(3.68)	(-2.54)	(-1.05)	(-3.76)
2	-0.40	1.01	0.52	-0.19	-0.39	-0.18
	(-2.36)	(39.34)	(7.10)	(-2.20)	(-3.32)	(-1.60)
3	0.02	0.99	0.75	-0.22	-0.16	0.06
	(0.11)	(39.44)	(10.55)	(-2.70)	(-1.35)	(0.58)
4	0.23	0.91	0.38	-0.32	-0.40	-0.37
	(1.05)	(26.79)	(3.95)	(-2.86)	(-2.57)	(-2.53)
5 (High *AIV*)	0.38	0.92	0.38	-0.49	-0.10	-0.40
	(1.60)	(25.61)	(3.76)	(-4.14)	(-0.61)	(-2.57)
High-Low	0.66	-0.05	0.10	-0.26	0.03	0.04
	(3.64)	(-1.82)	(1.28)	(-2.90)	(0.24)	(0.34)

Table A5. Cross-Sectional Return Forecasting Regressions using Poisson Regressions to Estimate *AIV*

This table reports predictive regressions of future stock returns. *LNVISIT* is the raw number of on-site investor visits for firm in the past three months. *AIV* is the residual value from a monthly regression of raw number of on-site investor visits for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). *ATOT* is the residual value from a monthly regression of log one plus number of analyst coverage for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), and cumulative returns in past 12 months (*MOMEN*), following Lee and So (2017). *SIZE* is the log of circulation market cap in million CNY. *BTM* is book-to-market ratio. *MOM12* is 12-month momentum except for the previous one month. *MOM1* is one-month momentum. *ROEQ* is quarterly operating income scaled by average total net asset. *AG* is year-over-year growth rate of total asset. *TURN1* is trading volume in last one-month scaled by circulation shares outstanding. *AVGSAR* is average of cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for the site visits that happened in past three months, following Cheng et al (2019). *HOLDPCT* is percentage of shares held by mutual funds based on latest available semiannual or annual mutual fund reports. Δ*HOLDPCT(LAG)* equals the change in mutual fund holding percentage in latest available semiannual period. Δ*HOLDPCT(FUT)* equals the change in mutual fund holding percentage in the next semiannual period. *AIV_NOFUND* is abnormal investor visits based on visit sample in which no visitor is from fund firms. All explanatory variables are standardized as zero mean and one standard deviation within each cross-section. We run cross-sectional regressions every calendar month, and the time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}
LNVISIT	0.142						
	(1.23)						
AIV		0.206***	0.134***	0.134***	0.130***	0.131***	0.082**
		(3.87)	(3.26)	(3.30)	(3.13)	(3.25)	(2.09)
ATOT			0.227**	0.229**	0.232**	0.239**	0.084
			(2.31)	(2.33)	(2.50)	(2.53)	(0.96)
SIZE			-0.863***	-0.864***	-0.870***	-0.852***	-0.917***
			(-3.14)	(-3.14)	(-3.08)	(-3.06)	(-3.50)
BTM			0.087	0.088	0.087	0.084	0.124
			(0.75)	(0.76)	(0.84)	(0.81)	(1.24)
MOM12			0.141	0.139	0.142	0.128	-0.104
			(1.10)	(1.10)	(1.14)	(1.02)	(-1.02)
MOM1			-0.492**	-0.493**	-0.494**	-0.500**	-0.678***
			(-2.55)	(-2.58)	(-2.61)	(-2.62)	(-3.35)
ROEQ			0.236***	0.235***	0.235***	0.239***	0.264***
			(3.23)	(3.23)	(3.26)	(3.36)	(4.09)
AG			-0.132***	-0.132***	-0.132***	-0.135***	-0.140***
			(-3.46)	(-3.49)	(-3.49)	(-3.62)	(-3.85)
TURN1			-0.747***	-0.750***	-0.756***	-0.757***	-0.647***
			(-9.89)	(-9.98)	(-10.18)	(-10.32)	(-8.38)
AVGSAR				0.010	0.017	0.015	-0.025
				(0.31)	(0.53)	(0.48)	(-0.75)
HOLDPCT					-0.003	-0.044	0.530***
					(-0.03)	(-0.52)	(4.57)
ΔHOLDPCT(LAG)						0.087**	0.115**
						(2.62)	(2.56)
ΔHOLDPCT(FUT)							1.061***
							(7.98)
Intercept	1.561	1.561	1.561	1.561	1.561	1.561	1.561
	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)
N	108,874	108,874	108,874	108,874	108,874	108,874	108,874
Avg. R^2	0.007	0.004	0.098	0.099	0.103	0.104	0.119

Table A6. Abnormal-Investor-Visit Strategy Using Total Number of Visiting Investors

Panel A reports Fama-MacBeth regression results on the determinants of on-site investor visits. *LNVISIT(NUM)* is log one plus number of the total number of visiting investors for firm in the past three months. *SIZE* is the log of circulation market cap in million CNY. *TURN* is average trading volume in past 12-month scaled by circulation shares outstanding. *MOMEN* is cumulative returns in past 12 months. *ROA* is operating income scaled by average total asset. All variables are winsorized within each cross-section at 1% and 99% levels. We run cross-sectional regressions every calendar month. The t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. Panel B reports calendar-time portfolio returns based on abnormal investor visits (*AIV*). *AIV* is the residual value from a monthly regression of log one plus the total number of visiting investors for firm in the past three months regressed on the log of firms' circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). *Raw* is monthly raw returns, *Market-adjusted* returns are raw returns minus sample average returns, and *DGTW-adjusted* returns are calculated following Daniel et al (1997). To construct this table, firms are ranked and assigned into quintile portfolios at the beginning of every calendar month based on *AIV*. All stocks are equally (value) weighted within a given portfolio, and portfolios are rebalanced every calendar month to maintain equal (value) weights. The *t*-statistics are reported in parentheses. Panel C reports equal- and value- weighted portfolio alphas adjusted by Fama-French Five-Factor Model based on *AIV*. Returns are measured in month *m+1*, where *AIV* is calculated and assigned to quintiles in month *m*. Alpha is the intercept from the time series regression of raw returns minus the risk-free rate, regressed on the five factor returns. Fama French factor returns are from CSMAR. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 through December 2019.

Panel A: Determinants of On-site Investor Visits				
	(1)	(2)	(3)	(4)
	LNVISIT(NUM)	*LNVISIT(NUM)*	*LNVISIT(NUM)*	*LNVISIT(NUM)*
SIZE	0.365***	0.415***	0.347***	0.299***
	(27.33)	(33.25)	(32.54)	(27.98)
TURN		0.288***	0.153***	0.126***
		(9.66)	(6.14)	(5.54)
MOMEN			0.481***	0.473***
			(11.80)	(12.59)
ROA				2.269***
				(30.10)
Intercept	-2.316***	-2.858***	-2.219***	-1.960***
	(-19.37)	(-26.90)	(-24.74)	(-22.26)
N	108,874	108,874	108,874	108,874
Adj. Avg. R^2	0.069	0.079	0.097	0.117

Panel B: One-Way Sorting Portfolios						
	Equal-Weighted Returns (%)			Value-Weighted Returns (%)		
	Raw	*Market-adjusted*	*DGTW-adjusted*	*Raw*	*Market-adjusted*	*DGTW-adjusted*
1 (Low *AIV*)	0.87	-0.70	-0.29	0.79	-0.35	-0.18
	(0.94)	(-3.88)	(-4.30)	(0.95)	(-2.82)	(-2.67)
2	1.23	-0.33	-0.18	0.91	-0.23	-0.13
	(1.18)	(-3.07)	(-2.57)	(0.92)	(-1.17)	(-1.50)
3	1.84	0.28	-0.05	1.45	0.31	-0.05
	(1.73)	(1.74)	(-0.65)	(1.42)	(1.24)	(-0.64)
4	1.96	0.40	0.17	1.45	0.30	0.10
	(1.83)	(2.09)	(2.16)	(1.64)	(1.63)	(0.77)
5 (High *AIV*)	1.92	0.35	0.35	1.44	0.30	0.25
	(1.83)	(2.09)	(3.01)	(1.57)	(1.69)	(2.31)
High-Low	1.05	1.05	0.64	0.65	0.65	0.43
	(4.64)	(4.64)	(4.25)	(2.65)	(2.65)	(2.82)

Panel C: Factor Model Adjusted Portfolios						
Equal-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.48	0.96	0.56	-0.09	-0.31	-0.51
	(-2.45)	(32.21)	(6.58)	(-0.94)	(-2.26)	(-4.01)
2	-0.38	1.02	0.80	-0.08	-0.30	-0.22
	(-2.32)	(40.90)	(11.31)	(-0.99)	(-2.66)	(-2.02)
3	0.19	0.99	0.93	-0.22	-0.09	0.13
	(1.29)	(43.69)	(14.51)	(-2.90)	(-0.87)	(1.34)
4	0.47	0.92	0.79	-0.25	-0.28	-0.14
	(2.71)	(34.62)	(10.52)	(-2.84)	(-2.32)	(-1.22)
5 (High *AIV*)	0.47	0.98	0.79	-0.33	-0.12	-0.55
	(2.07)	(27.85)	(7.94)	(-2.86)	(-0.73)	(-3.68)
High-Low	0.95	0.01	0.23	-0.24	0.19	-0.04
	(6.43)	(0.62)	(3.59)	(-3.18)	(1.83)	(-0.40)
Value-Weighted:	Alpha	MKT	SMB	HML	RMW	CMA
1 (Low *AIV*)	-0.32	0.96	0.28	-0.17	-0.26	-0.48
	(-1.85)	(36.33)	(3.71)	(-1.96)	(-2.17)	(-4.24)
2	-0.53	1.03	0.56	-0.12	-0.38	-0.18
	(-2.80)	(35.49)	(6.81)	(-1.28)	(-2.84)	(-1.44)
3	-0.04	1.02	0.72	-0.30	-0.11	0.15
	(-0.27)	(40.62)	(10.11)	(-3.60)	(-0.96)	(1.391)
4	0.30	0.89	0.35	-0.24	-0.46	-0.36
	(1.27)	(24.98)	(3.47)	(-2.02)	(-2.80)	(-2.38)
5 (High *AIV*)	0.40	0.95	0.40	-0.61	0.08	-0.37
	(1.67)	(26.19)	(3.89)	(-5.14)	(0.46)	(-2.38)
High-Low	0.72	-0.01	0.12	-0.44	0.34	0.11
	(3.77)	(-0.46)	(1.45)	(-4.61)	(2.55)	(0.89)

Table A7. Cross-Sectional Return Forecasting Regressions Using Total Number of Visiting Investors

This table reports predictive regressions of future stock returns. *LNVISIT(NUM)* is the log of the total number of visiting investors for firm in the past three months plus one. *AIV* is the residual value from a monthly regression of log one plus the total number of visiting investors for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), cumulative returns in past 12 months (*MOMEN*), and return on total asset (*ROA*). *ATOT* is the residual value from a monthly regression of log one plus number of analyst coverage for firm in the past three months regressed on firm's circulation market cap (*SIZE*), average monthly turnover in past 12 months (*TURN*), and cumulative returns in past 12 months (*MOMEN*), following Lee and So (2017). *SIZE* is the log of circulation market cap in million CNY. *BTM* is book-to-market ratio. *MOM12* is 12-month momentum except for the previous one month. *MOM1* is one-month momentum. *ROEQ* is quarterly operating income scaled by average total net asset. *AG* is year-over-year growth rate of total asset. *TURN1* is trading volume in last one-month scaled by circulation shares outstanding. *AVGSAR* is average of cumulative size-adjusted returns in the 2-day event window (i.e., [0, +1]) for the site visits that happened in past three months, following Cheng et al (2019). *HOLDPCT* is percentage of shares held by mutual funds based on latest available semiannual or annual mutual fund reports. Δ-*HOLDPCT(LAG)* equals the change in mutual fund holding percentage in latest available semiannual period. Δ*HOLDPCT(FUT)* equals the change in mutual fund holding percentage in the next semiannual period. *AIV_NOFUND* is abnormal investor visits based on visit sample in which no visitor is from fund firms. All explanatory variables are standardized as zero mean and one standard deviation within each cross-section. We run cross-sectional regressions every calendar month, and the time-series standard errors are Newey-West adjusted (12 lags) for heteroskedasticity and autocorrelation. The *t*-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively. The sample for this analysis consists of 108,874 firm-month observations spanning July 2012 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}	RET_{m+1}
LNVISIT(NUM)	0.120						
	(0.97)						
AIV		0.259***	0.173***	0.172***	0.168***	0.168***	0.119***
		(4.27)	(4.10)	(4.12)	(3.97)	(4.01)	(3.23)
ATOT			0.210**	0.212**	0.216**	0.224**	0.070
			(2.18)	(2.21)	(2.40)	(2.44)	(0.82)
SIZE			-0.865***	-0.866***	-0.870***	-0.852***	-0.917***
			(-3.15)	(-3.15)	(-3.09)	(-3.07)	(-3.50)
BTM			0.095	0.095	0.094	0.091	0.129
			(0.82)	(0.83)	(0.91)	(0.88)	(1.30)
MOM12			0.142	0.140	0.143	0.129	-0.102
			(1.11)	(1.10)	(1.14)	(1.02)	(-1.00)
MOM1			-0.491**	-0.492**	-0.492**	-0.498**	-0.676***
			(-2.54)	(-2.57)	(-2.59)	(-2.60)	(-3.34)
ROEQ			0.242***	0.241***	0.241***	0.245***	0.269***
			(3.30)	(3.30)	(3.34)	(3.43)	(4.14)
AG			-0.131***	-0.132***	-0.131***	-0.134***	-0.139***
			(-3.38)	(-3.41)	(-3.41)	(-3.54)	(-3.77)
TURN1			-0.747***	-0.750***	-0.756***	-0.757***	-0.648***
			(-9.87)	(-9.96)	(-10.15)	(-10.29)	(-8.37)
AVGSAR				0.007	0.013	0.012	-0.029
				(0.21)	(0.42)	(0.37)	(-0.86)
HOLDPCT					-0.006	-0.048	0.527***
					(-0.07)	(-0.57)	(4.55)
ΔHOLDPCT(LAG)						0.088***	0.116**
						(2.66)	(2.56)
ΔHOLDPCT(FUT)							1.057***
							(7.96)
Intercept	1.561	1.561	1.561	1.561	1.561	1.561	1.561
	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)	(1.60)
N	108,874	108,874	108,874	108,874	108,874	108,874	108,874
Avg. R^2	0.008	0.005	0.098	0.099	0.103	0.104	0.119

Table A8. Differences between the SZSE & the SHSE

This table report a summary of the differences between stock market of the SZSE and the SHSE. Panel A gives a timeline of the development history of the SHSE and the SZSE. Panel B presents a summary for the key statistics data of the SHSE stock market and the SZSE stock market at March 11, 2024. The sample includes all SHSE/SZSE listed firms. Data come from the official websites of the SHSE and the SZSE. Panel C summarizes the different market characteristics of the SHSE and the SZSE. Panel D summarizes the disclosure differences between the SZSE and the SHSE.

Panel A: History of Development	
Time	Event
1990.11	The SHSE was established as the first stock exchange in mainland China.
1990.12	The SZSE was established.
2004.06	The SZSE launched small and medium-sized board to encourage innovation.
2009.10	The SZSE launched second-board market to support growing entrepreneurial firms and the development of emerging industries.
2019.06	The SHSE launched the science and technology innovation board.
2021.04	The SZSE main board and small and medium-sized board officially merged.

Panel B: Descriptive Statistics of Stock Market of the SHSE & the SZSE (at March 11, 2024)		
Variable	SHSE	SZSE
# of listed companies	2,271	2,848
Total market value (billion RMB)	47,707.42	29,704.97
Average market value (billion RMB)	21.01	10.43
Average P/E ratio	12.33	20.89
Average turnover	0.90	2.14

Panel C: Different Characteristics of the SHSE & the SZSE		
	SHSE	SZSE
Firm size	Larger	Smaller
Market structure	Dominated by blue-chip stocks, including large state-owned enterprises and well-known listed companies	With larger number of small and medium-sized enterprises in addition to large, stable companies
Industries	More of traditional industries such as finance, real estate, and manufacturing	More of emerging industries such as high-tech, electronics, and medicine
Activity	More conservative	More active and volatile

Panel D: Disclosure Differences between the SZSE & SHSE		
Topic	SZSE	SHSE
Site visits (Cheng et al., 2016; Cheng et al., 2019; Bowen et al., 2018)	In 2008, the SZSE mandated that all listed firms disclose the summary information about every site visit in their annual reports starting from 2009. The disclosure of site visits is strictly enforced. The SZSE publicly denounces firms that fail to disclose site visit information.	The SHSE does not require disclosure of investor visit activities of firms listed on the SHSE main board.
	From July 2012, the Shenzhen Stock Exchange required all listed firms to electronically publish a standard meeting report for each investor visit through its web portal, Hu Dong Yi, within two trading days of the visit date.	From 2020, the SHSE requires listed firms on the Science and Technology Innovation Board to release investor site visit information through e Hu Dong every month.
Internet-based communication platform (Lee and Zhong, 2022; Wang et al., 2022)	In January 2010, the Hu Dong Yi platform was launched.	In July 2013, the e Hu Dong platform was launched.
	In November 2011, an upgraded version of Hu Dong Yi based on the Web 2.0 platform was launched.	
The assessment methods for information disclosure (Wang et al., 2022)	In November 2011, the assessment methods for information disclosure on the SZSE (2011 Revision) were released. The 2011 revised assessment methods for information disclosure increase the regulatory requirements for Hu Dong Yi platform.	In October 2013, the assessment methods for information disclosure on the SHSE (Trial) were released, which include the communication between listed firms and investors through the e Hu Dong platform in the assessment.
	The SZSE evaluates listed firms' information disclosure, and discloses it to the public.	The SHSE evaluates listed firms' information disclosure, but not to the public.
Corporate social responsibility (Lin, 2010; Wang et al., 2013)	In September 2006, the SZSE issued the *Guidelines*, which became the first regulatory system on social responsibility disclosure in the Chinese capital market. However, the Guidance is not mandatory and only encourages listed firms to establish relevant institutional systems to disclose external CSR reports and publish environment-related information.	The SHSE did not have disclosure requirements for social responsibility reporting before 2008.
	In December 2008, the SHSE and the SZSE simultaneously issued the Notice on the Work of 2008 Annual Reports of Listed Firms, which required firms listed on the SHSE Corporate Governance Index, firms issuing overseas-listed foreign shares, and financial firms to disclose CSR reports, and required listed firms included in the SZSE 100 Index to disclose CSR reports, and encourages other firms to disclose CSR reports.	