Foreign Capital in the Chinese Stock Market: A Firm-Level Study

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Abstract

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JEL: G12, G14, G15, G18

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Using a proprietary dataset covering all foreign investors' daily trades in the Chinese stock market from 2016 to 2019, we find that foreign order flows, facilitated by regulatory liberalization through several channels, present strong predictive power for future stock returns, implying that these order flows are likely informed. We track the source of this informativeness and find that foreign order flows significantly predict firm-level news and news-day returns, which suggests that foreign investors can process local firm information. Finally, regulatory reforms that generally relax investment access requirements further improve foreign investors' predictive power.

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I. Introduction

Many studies show that foreign capital plays a significant and positive role in spurring the development of emerging stock markets. For example, foreign capital helps to lower firms' capital costs (Bekaert and Harvey (2000)), spur economic growth (Bekaert, Harvey, and Lundblad (2005)), facilitate cross-border mergers and acquisitions (Ferreira, Massa, and Matos (2010)), promote corporate governance (Ferreira and Matos (2008), and Aggarwal, Erel, Ferreira, and Matos (2011)), expedite global information transmission (Bae, Ozoguz, Tan, and Wirjanto (2012)), and improve price efficiency (Kacperczyk, Sundaresan and Wang (2021)). However, there are still two key open questions in the literature on foreign capital: whether and how foreign capital contributes to local price discovery and informational efficiency.

First, there is mixed evidence regarding whether foreign investors predict local stock returns and contribute to local price discovery. On one side, Kang and Stulz (1997) show that holdings of foreign investors do not predict monthly stock returns in Japan, possibly because foreign investors tend to hold large-firm stocks that have low expected returns; Hau (2001) finds that foreigners have trading losses in Germany, suggesting that foreign investors face informational disadvantages caused by geographic barriers; Dvořák (2005) also shows foreign investors perform poorly in Indonesia.[1] Conversely, Grinblatt and Keloharju (2000) find that foreign investors display positive investment performance in Finland, possibly because foreign investors are more sophisticated than locals and possess informational advantages. A few studies

[1] Agarwal, Faircloth, Liu, and Rhee (2009) suggest that the foreign investors' poor performance in Indonesia is due to their aggressive trading behaviors. Teo (2009) shows that hedge funds distant from their investment region underperform their counterparties. Other research, which does not focus on return predictability, implies that foreign investors may be disadvantaged in the local market. For example, Choe, Kho, and Stulz (2005) show that foreign money managers in South Korea pay higher transaction costs than local investors, which they interpret as a result of foreign investors' tendency to trade against stock price changes.

focus on the predictive power of international capital flows at the market level, but also provide mixed results. For instance, Brennan and Cao (1997) find that U.S. investors are disadvantaged in emerging markets, while Froot, O'Connell, and Seasholes (2001) show evidence on the opposite side.

Second, there is surprisingly little *direct* evidence on how foreign investors obtain their return predictive power, which would link their activities to local information efficiency. A few studies suggest that foreign investors might have informational advantages, but they only offer *indirect* evidence. For instance, Bailey, Mao, and Sirodom (2007) find that foreign trades significantly increase during and after earnings announcements in Thailand, indicating foreign investors might be able to process local information; Froot and Ramadorai (2008) show that the responses to price and net-asset-value returns for closed-end country funds are roughly of the same magnitude, suggesting that cross-border flows are linked to fundamentals at the market level. Because there is no definite answer to whether foreign capital flows can predict local returns and there is no direct evidence of how foreign investors process local information, the fundamental mechanism of how foreign investors facilitate local stock price discovery and local information efficiency (Kacperczyk et al. (2021)) appears unclear.

Our study fills in the blanks by *directly* examining whether and how foreign order flows predict firm-level returns in the cross-section of local Chinese A-share market stocks with detailed, high-frequency trade data. To be exact, we utilize a proprietary dataset of investors' daily trading records from 2016 to 2019, which includes all foreign order flows at the stock level. This dataset also provides data on order flows from local institutions, such as mutual funds, hedge funds, and others, which we use as benchmarks for comparison purposes. More importantly, we build a direct connection between trading with firm-level information events and the environment. The detailed nature of our data allows us to answer long-standing questions that are interesting and particularly important for the general international investment community. Meanwhile, given that the Chinese equity market is collectively the second largest in the world and plays an increasingly important role in global asset allocation, the relevance of the Chinese market is also significant in and of itself.

Before we move on to the empirical results, we briefly introduce the institutional background. Over the past 20 years, regulators from China, clearly recognizing the benefits of foreign capital, consistently invited foreign investors to participate in the development of the Chinese stock market. Three major channels were created to allow foreign capital access to domestic Chinese equity A-shares. First, the Qualified Foreign Institutional Investors (QFII) program, launched in November 2002, allows foreign institutional investors to trade equities and other financial instruments by converting foreign currencies into onshore RMB. Second, the Renminbi QFII (RQFII) program, introduced in December 2011, permits qualified overseas institutional investors to invest in the domestic capital market using offshore RMB directly. Third, and most recently, the Hong Kong Stock Connect (HKC) programs, linking the Hong Kong stock market with the Chinese mainland stock market, were launched in 2014. HKC enables Hong Kong and overseas individual and institutional investors to trade eligible Chinese A-shares. By the end of 2021, foreign investors held around RMB 3.67 trillion in A-shares through these channels, collectively accounting for 4.97% of A-share aggregate market capitalization.

First, we provide direct evidence of whether foreign capital flows predict local firm-level returns. Taking QFII as an example, we find that an interquartile increase in daily QFII order flow is associated with an 11.88 bps increase in the next day's stock return (or 29.94%

annualized), with a highly significant *t*-statistic of 17.03. When we turn to RQFII and HKC, an interquartile increase in daily order flows is associated with 3.05 bps and 7.57 bps increases, respectively, in the next day's return (or 7.69% and 19.08% annualized). For comparison, an interquartile increase in daily local institutional order flow is associated with a 9.33 bps increase in the next day's return (or 23.51% annualized). Taking these figures together, foreign investors' trading activity significantly predicts future local stock returns, and their predictive power is on par with that of their local institutional counterparts. When we extend the prediction window from days to weeks, foreign investors significantly predict cumulative stock returns over at least the next 12 weeks, implying that the information in their trading flows is not transient.[2]

There are alternative and non-exclusive hypotheses for foreign capital flows, including the diversification and liquidity hypotheses. As discussed in Van Nieuwerburgh and Veldkamp (2010), the diversification hypothesis states that the capital flows from investors adopting diversification strategies in opening emerging markets have less return predictive power for future stock returns. The strong evidence of foreign capital flows' predictive power for future returns doesn't support the diversification hypothesis. The liquidity hypothesis is more complicated. On the one hand, as discussed in Richards (2005), if foreign investors' trading is persistent, their trading might generate price pressures, leading to higher future prices, consistent with a positive predictive relation between foreign capital flows and future returns. On the other hand, as suggested by Barrot, Kaniel, and Sraer (2016), if foreign investors' trading follows a contrarian pattern, where foreign investors buy more when prices are lower, they provide

[2] Readers may wonder if both local and foreign institutional investors positively predict returns, who are their counterparties? Our data show that more than half of the counterparties for foreign investors are local retail investors, and the predictive power of foreign investors' trades is stronger when they trade against retail investors than local institutions.

liquidity to the market. They would be compensated by the subsequent positive returns to their buy orders. Our empirical results show that price pressures and contrarian trading from foreign investors might not be the main reasons for foreign investors' return predictive power. Collectively, using detailed data heretofore unavailable to researchers, we provide definitive evidence that foreign capital flows predict local returns and contribute to local price discovery.

Next, given that foreign order flows strongly predict stock returns in the cross-section, we build direct connections between foreign capital flows and firm-level information to understand whether foreign investors contribute to local informational efficiency. We build a broad dataset on important firm-level information events, such as earnings announcements, analyst reports, and media news. We present clear evidence that foreign order flows significantly predict future firm-level news. Although the prior literature suggests that physical distance and language barriers may make it difficult for foreign investors to process local firm-level news, our results indicate that foreign investors seem able to process local firm-level information. In addition, we collect anecdotal evidence that foreign investors adopt effective strategies to overcome language and culture barriers. For instance, they are stationed in or close to China and hire the best local professionals to manage their portfolios.

Moreover, for firms with a better information environment, where information becomes more accessible to foreign investors and where information acquisition costs are lower, foreign investors with skills and resources may predict future stock returns even better. Using analyst coverage as a proxy for the information environment, we find that foreign investors have more substantial return predictive power on stocks covered by more analysts. We also provide evidence that foreign investors' return predictive power is stronger for firms with more cross-border business, which indicates that foreign investors might have information advantages for firms more involved in global business networks. Finally, over our four-year sample, Chinese regulatory authorities gradually relaxed the restrictions on foreign capital, allowing better access for foreign investors to participate in the Chinese stock market. Our empirical results suggest that expanding investment quotas and capital flows may contribute to foreign investors' return predictive power (at least at the reform levels we observe). Overall, our study directly connects foreign capital flows' predictive power to local firm-level information and the local information environment and provides direct evidence that foreign investors contribute to local informational efficiency.

In comparison with the existing literature, our paper provides four new insights. First, our research contributes to resolving the ongoing debate about foreign investors' return predictability by examining the return predictive power of foreign order flows with different hypotheses. Second, prior research examines whether foreign investors' trading is informed *indirectly*. Using detailed transaction data and firm-level information, we connect foreign investors' trading to various types of news and *directly* analyze whether foreign investors are informed about local informational events. Third, our data's richness allows us to compare trading patterns between foreign investors and local institutions, improve on previous studies with a focus on overall institutional trading,[3] and provide a better understanding of overseas investors' skills when compared to domestic investors. Finally, we are one of the first studies to provide comprehensive evidence on the trading behavior of foreign investors in China, spanning QFII, RQFII, and HKC, and their information content. A few studies on foreign investors in the Chinese stock market

[3] There is also a sizeable literature using U.S. data to examine institutional investors' informational advantages over public information. For example, Irvine, Lipson, and Puckett (2007) find that institutional trades before analyst recommendation releases earn abnormal profits. Campbell, Ramadorai, and Schwartz (2009) show that institutional trades predict earnings surprises. Hendershott, Livdan, and Schürhoff (2015) show that institutional investors are informed about news content. Huang, Tan, and Wermers (2020) find that institutions can trade correctly on news tone after the earliest news release.

(e.g., Chen, Wang, and Zhu (2024), and Bian, Chan, Han, and Shi (2023)) only focus on HKC investors with publicly available data.[4] Overall, our findings on the predictive patterns of various foreign investors and their information-processing skills are important for academic researchers, industry practitioners, and regulators.

II. Hypothesis Development

To guide our empirical analysis, we first develop hypotheses about whether foreign investors have return predictive power for cross-sectional stock returns. We measure foreign investors' trading behavior by their order flows, which are widely used in studies on retail investors (Bailey, Cheung, and Wang (2009), Kelley and Tetlock (2013), Barrot et al. (2016), and Boehmer, Jones, Zhang, Zhang (2021)) and institutional investors (Hendershott et al. (2015)). Because the prior literature provides little direct evidence on the relation between foreign order flows and local stock returns, the answer to this question remains unknown. On the one hand, given the relatively low correlation with developed market returns, foreign investors may hold Chinese A-share stocks for diversification purposes. As suggested by Van Nieuwerburgh and Veldkamp (2010), if investors follow a simple diversification strategy, they don't necessarily have an informational advantage and might be unable to predict future returns. Therefore, the diversification hypothesis suggests that foreign investors' trade flows might not predict stock returns if they invest for diversification purposes. On the other hand, foreign investors are mostly attached to high-powered and well-resourced global institutions, and they

[4] Existing studies also examine other aspects of foreign investors in China, such as information asymmetry (Chan, Menkveld, and Yang (2008), corporate governance (Huang and Zhu (2015)), reactions to analysts' recommendation (Jia, Wang, and Xiong (2017)), firm disclosure (Yoon (2021)), corporate activity (Ma, Rogers, and Zhou (2021)) and Chinese mainland insider trading in HKC (He, Wang, and Zhu (2022)). Using a similar dataset from the Shanghai Stock Exchange, Bailey et al. (2009) find that institutional order imbalance has a large contemporaneous price impact on stocks. Different from their study, our paper focuses on foreign investors' trading and investigates their predictive power and the sources of their informational advantages.

might have considerable advantages in information processing. Albuquerque, Bauer, and Schneider (2009) show that in a model where global investors possess valuable private information for trading in many countries, their trading flows are positively related to local returns. The information hypothesis implies that foreign order flows predict stock returns, particularly for those stocks on which foreign investors have significant informational advantages. Finally, foreign capital flows into the local market might affect the liquidity condition and lead to predictive patterns for future returns. On the one hand, as discussed in Richards (2005) and Ferreira, Matos, and Pires (2017), persistent capital inflows from foreign investors are demand shocks for local stocks. They can generate price pressures and positively predict future returns. On the other hand, Barrot et al. (2016) show that investors can be compensated by providing liquidity in the market. If foreign investors supply liquidity by following a contrarian strategy, their order flows predict future returns and would be compensated for liquidity provision.

We summarize these competing hypotheses for foreign capital flows' predictive power for future returns as follows:

H1a. (Diversification Hypothesis) Foreign capital flows do not predict cross-sectional stock returns in the Chinese A-share market if these investors mainly invest for diversification purposes.

H1b. (Information Hypothesis) Foreign capital flows predict cross-sectional stock returns in the Chinese A-share market if these investors are informed investors in Chinese firms.

H1c. (Liquidity Hypothesis) Foreign capital flows predict cross-sectional stock returns in the Chinese A-share market if these investors generate price pressures and/or provide liquidity to the local market.

Given that our later empirical results are more consistent with the information hypothesis and that one key open question in the literature is to understand the direct relation between foreign investors' trading and firm-level information, our second hypothesis is developed around this question. We hypothesize that the strong predictive power of foreign investors for future returns might be rooted in their information collection and processing skills. If true, their order flows should predict firm-level news, such as earnings surprises, analyst updates, and media news. If not, foreign order flows shouldn't predict firm-level news.

H2. Foreign capital flows can predict firm-level news.

Finally, we hypothesize that foreign investors' return predictive power may be related to firms' informational environment. On the one hand, according to Fernandes and Ferreira (2008) and Harford, Jiang, Wang, and Xie (2019), firms with a better information environment may have more information available, and the information acquisition costs might be lower for these firms. Foreign capital's predictive power may be stronger for firms with a better information environment. However, Easley, Hvidkjaer, and O'Hara (2002) and Easley and O'Hara (2004) point out that firms with lower information risks also have lower compensation for information acquisition activities. If true, foreign investors' return predictive power might be weaker on stocks with a better information environment.

H3. Foreign capital flows' predictive power for returns is higher for firms with a better information environment.

By testing these hypotheses, we obtain general findings on foreign investors' return predictive power in the local market, which are helpful for the general setting of the global capital market.

III. Institutional Background and Data

A. Foreign Investors in the Chinese Stock Market

Foreigners mainly invest in the Chinese onshore stock market through three programs: QFII, RQFII, and HKC. As investment channels for foreign capital, the three programs share common goals yet differ in several aspects, such as investor eligibility, investment scope, and capital control, which may lead to distinctive trading patterns in the Chinese stock market.[5]

We summarize the key differences in Table 1. First, in terms of investor eligibility, QFII and RQFII include only foreign institutional investors, whereas HKC includes both individual and institutional investors from both Hong Kong and overseas areas. It is worth noting that foreign investors through QFII must meet certain thresholds on assets under management and operational durations. As a result, most of the QFIIs are large and renowned institutions in global capital markets, such as Barclays Bank and Goldman Sachs. In contrast, RQFII was created in 2011 to expedite offshore RMB business, and it was only available to Hong Kong subsidiaries of domestic financial institutions (such as China Asset Management HK) and foreign institutional investors (such as Fidelity HK).[6] Therefore, especially in its early stages, the RQFIIs include many institutions intending to spend offshore RMBs, rather than pursuing superior investment performance. The HKC program provides access for both institutional investors and retail investors, with international asset management companies (e.g., J.P. Morgan China A-share Funds) and overseas brokers backed by hedge funds being the main HKC investors, and retail trading accounting for only a small portion of the HKC program.[7] Given the small proportion of

[5] It is possible that some foreign institutions access the Chinese stock market through multiple programs, and they might strategically optimize their use of the three programs.
[6] See http://www.safe.gov.cn/safe/glxx1/index.html for a complete QFII and RQFII list.
[7] From the speech of Fang Xinghai, the vice chairman of China Security Regulation Commission, on April 19, 2021.

retail investors through the HKC program, we treat the HKC order flows as representative of institutional investors in later discussions.[8]

Second, foreign investors from different channels are subject to different capital control regulations. For most of our sample, QFIIs and RQFIIs are subject to a 3-month lock-up period to promote long-term involvement. QFIIs can only repatriate investment principal and profits monthly, up to 20% of the previous year's total assets. Capital inflow and outflow, however, are not a concern for HKC investors, meaning that they can more easily enter and exit the Chinese domestic market over short periods. Therefore, QFIIs and RQFIIs presumably have lower turnovers and focus more on long-term returns than HKC investors. In addition, there are investment quotas on individual QFII/RQFII/HKC investors and certain aggregate restrictions across all program participants. To lower the regulation costs on foreign investors, the quotas are generally set at relatively high numbers (and are often not binding).

Third, the eligible stocks differ across the QFII, RQFII, and HKC programs. QFIIs and RQFIIs can invest in all A-share stocks listed on exchanges, fixed-income securities, and other financial products. In contrast, HKC investors can only trade the constituent stocks of specific stock indices and the A shares with H shares listed on the Hong Kong Stock Exchange. The broad scope of financial instruments available for QFII and RQFII may attract large asset management companies with multi-asset investment demand and institutions that use derivatives to control risks or perform complex strategies. To ensure that foreigners do not own too large a

[8] QFII, RQFII, and HKC are channels through which foreign capital outside of Mainland China can access the Chinese A-share market. Some readers might be curious about the citizenship of these investors or whether they are really "foreigners." Our opinion is that the capital *per se*, not the capital managers, is more important for the development of the market. Therefore, the focus of our study is how "foreign capital", money from outside the country, behaves in the Chinese stock market. We leave the question of identifying the citizenship of money managers of the "foreign capital" to other studies.

share of A-share stocks, there is an upper limit in the sense that all three types of foreign investors combined cannot hold more than 30% of a firm’s total shares outstanding.

[Insert Table 1 here]

Because of these differences, foreign investors in the three programs may have different trading patterns and investment skills. Given the stricter eligibility requirements, tighter restrictions on capital flows, and broader investment scope, QFIIs are likely to be sophisticated investors, focusing on long-term performance and fundamentals. In comparison, given the capital controls, RQFIIs are also likely to be long-term investors. Still, they may be less sophisticated because many are Hong Kong subsidiaries whose primary goal is the absorption of offshore RMB. The HKC investors are not subject to strict capital controls and can trade more freely over short horizons, so their investment horizon could be shorter.

Figure 1 presents the regulation changes related to investment quotas, capital controls and investment accessibility since 2002. Take QFII as an example. When the program was first introduced in 2002, the investment quota was less than $10 billion. It was progressively raised to $300 billion in 2019 and finally lifted. Regarding capital repatriation, in 2012, the total amount of funds a QFII remits monthly cannot be more than 20% of the investor's total assets as of the preceding year's end. In June 2018, the limitations were lifted. Additionally, QFII was required to allocate at least 50% of its portfolio into equities; however, in September 2016, that restriction was lifted. Overall, the market liberalization process offers us a unique opportunity to examine the impact of liberalization on the evolution of foreign investors' behavior.

[Insert Figure 1 here]

B. Data

Our proprietary dataset comes from a major Chinese stock exchange. It includes all foreign investors' daily trading and holding from January 1, 2016, to June 30, 2019, and is not publicly available. We obtain other stock trading data and financial accounting information from WIND, a widely used Chinese financial database. As in Liu, Stambaugh, and Yuan (2019), we exclude stocks with less than 15 non-zero volume trading days in the past month to eliminate the influence of long-trading suspensions. After merging investors' trading information with the WIND data, we obtain a sample of approximately 1.1 million stock-day observations for over 1,200 stocks and 849 trading days.

For each stock each day, we collect buy and sell data for different groups of investors. Given that most foreign investors are institutional investors, we also collect information on local institutional investors to serve as a comparison benchmark. For our purposes, local institutional investors include mutual funds, hedge funds, insurance companies, security companies, trust companies, and other institutional investors. We rely on investor order imbalance data to measure their trading activities. Following Boehmer et al. (2021), we compute investor group G's order imbalance for stock i on day d as follows:

(1)
$$Oib(i,d,G) = \frac{Buyvol(i,d,G) - Sellvol(i,d,G)}{Buyvol(i,d,G) + Sellvol(i,d,G)},$$

where $Buyvol(i,d,G)$ and $Sellvol(i,d,G)$ represent the total number of shares bought and sold by all investors within group G. The variable $Oib(i,d,G)$ captures the trading direction of the investor group G for this stock, and its value varies between -1 and 1. A positive number means that a particular group of investors buy more than sell, and a negative number means that this group of investors sell more than buy. The order imbalance variable is set to missing when there is no stock trading on that day.

C. Summary Statistics

We present summary statistics in Table 2. Panel A reports foreign investors' and local institutions' trade and holding data. One special feature of the Chinese stock market is that retail investors contribute 80% of daily trading volumes over our sample period, so institutional investors, foreign and local, only account for about 20% of daily trading volumes. For average daily trading volumes, QFII, RQFII, and HKC investors account for 0.79%, 0.08%, and 2.24% of market daily volume, respectively, while local institutional investors account for 14.80%. These statistics indicate that QFII and HKC investors, as well as local investors, are relatively more active in trading, whereas RQFII investors tend to trade less frequently. The QFII, RQFII, and HKC investors trade 946, 174, and 561 stocks per day. Similar to trading, the holdings of the QFII, RQFII, and HKC investors account for 0.95%, 0.23%, and 1.20% of market floating capitalization, and the number of stocks held ranges between 744 for HKC and 1,261 for QFII.

[Insert Table 2 here]

We report the time series of foreign investors' aggregate trading and holding in Figure 2. The trading volume and holdings of QFIIs and RQFIIs are relatively stable. HKC becomes considerably more important over time, steadily increasing trading volume and holdings.

[Insert Figure 2 here]

Clearly, there are significant differences in the number of stocks traded and held by different groups of foreign investors. The low number of stocks for RQFII may result from their lower quotas and conservative strategies, while the lower number for HKC results from the scope of eligible stocks for investments. For our later empirical analysis, following Kelly and Tetlock (2013), if for a particular stock, there is no trading from a particular group of investors on a particular day, then the observation is set to missing and is then dropped from our empirical estimation.[9] Given the nature of the raw data, we maximize the number of observations for our empirical analysis to best capture all non-missing information in the raw data, and we always present the number of observations for each analysis. We also acknowledge the potential problem of comparability of coefficients across different groups, given the different number of observations, and therefore conduct robustness checks in the last section of the paper, where we only include stocks with non-missing data from all foreign investors, including QFII, RQFII, and HKC.

Since our study focuses on the cross-sectional trading behavior of foreign investors, Table 2 Panel B reports the time-series average of cross-sectional statistics on the order imbalance measure. The means of order imbalance for QFII, RQFII, and HKC are, respectively, -0.01, 0.02, and 0.02, with standard deviations at 0.86, 0.82, and 0.58. For one individual stock, the trades may be concentrated in one direction, causing the order imbalance measure to take values close to 1 or -1, which leads to the relatively large cross-sectional variation in QFII and RQFII order flows. In comparison, the mean of the order imbalance for local institutions is -0.01 with a standard deviation of 0.47, indicating that domestic investors' trading dispersion across stocks is smaller than that of foreign investors. The last column reports the cross-sectional mean of the first-order autocorrelation of the order imbalance measure. The coefficients are 0.09, 0.44, 0.12, and 0.18 for QFII, RQFII, HKC, and local institutions, respectively, which suggests that RQFIIs display a more persistent trading propensity than other investors. In the last three columns, we report the time-series average of the cross-sectional correlation coefficients for order imbalance measures across the four investor groups. The order imbalances of all investor

[9] In a robustness check, we consider replacing missing variables with zero. These results are discussed in Section V.E. We find foreign investors still significantly predict future stock returns.

groups are positively correlated, implying that trades from different types of investors may overlap to some extent. However, the correlations are generally lower than 0.14, indicating that investors' trading behaviors differ across groups.

IV. Empirical Results

A. Understanding Foreign Investors' Trading and Holding

We start our analysis by understanding foreign investors' trading and holding dynamics. First, we link foreign order flows to firm-level variables, such as previous returns and firm characteristics. We adopt the two-stage Fama-MacBeth (1973) regression method. For the first stage, for each day d, we estimate the following cross-sectional regression:

$$Oib(i,d,G) = a0(d,G) + a1(d,G)Ret(i,d-1) + a2(d,G)Ret(i,d-6,d-2) + \\ + a3(d,G)Ret(i,d-27,d-7) + a4(d,G)Oib(i,d-1,G) + \\ a5(d,G)'Controls(i,d-1) + \epsilon(i,d,G). \tag{2}$$

The dependent variable $Oib(i,d,G)$ is the order imbalance for stock i on day d for investor group G. To understand whether the foreign investors follow a momentum trading pattern or a contrarian pattern, we first include the previous stock returns over different horizons, where $Ret(i,d-1)$ represents the previous day return, $Ret(i,d-6,d-2)$ represents the previous week's return, and $Ret(i,d-27,d-7)$ represents the previous month's return. Positive coefficients on past return variables indicate that foreign capital flows increase if previous returns are high and is typically referred to as a "momentum" trading strategy, potentially demanding liquidity. Negative coefficients on previous returns indicate that foreign capital flows decrease if previous returns are high and are referred to as "contrarian" trading, which potentially provides liquidity and is presumably rewarded. We also estimate the persistence of the foreign capital flows by including its own lag, $Oib(i,d-1,G)$. If the order flow is persistent, the coefficient would be positive and vice versa. For the control variables, we include the usual suspects: log firm size ($Lnsize$) from the previous month-end, the firm's earnings to price ratio (EP) as the ratio of most recently reported quarterly earnings to the market capitalization from the previous month-end, and turnover ($Turnover$) as the ratio of monthly trading volume to floating A shares from the previous month-end. From the first stage estimation, we obtain a time series of the cross-sectional coefficients $\{\widehat{a0}(d,G), \widehat{a1}(d,G), \dots, \widehat{a5}'(d,G)\}$. In the second stage, we compute the time series averages as $\{\widehat{a0}(G), \widehat{a1}(G), \dots, \widehat{a5}'(G)\}$, and conduct inference using the time series of these coefficients. The standard errors are calculated using the Newey and West (1987) methodology with five lags, the optimal lag number under the Bayesian information criterion.

The results are reported in Table 3 Panel A. We first focus on the coefficients on past returns. The coefficients on $Ret(d-1)$ are -4.6313, -0.7709, -2.1991, and -1.8838 for QFII, RQFII, HKC, and local institutions, respectively, which means that over the one-day horizon, all foreign investor groups and local institutions are, on average, contrarian. Interestingly, coefficients on $Ret(d-6, d-2)$, and $Ret(d-27, d-7)$ are significantly negative for QFII, but significantly positive for RQFII and HKC. That is, QFII investors constantly pursue a contrarian strategy, while RQFII and HKC investors follow momentum over longer horizons. Local institutions' order flows are not significantly related to past returns over longer horizons. These findings share some commonality with earlier studies. For instance, Richards (2005) shows that foreign investors tend to be positive feedback traders in Asian emerging markets at the *market* level. Boehmer et al. (2021) find that marketable retail order flows in the U.S. follow contrarian strategies. We also find positive and significant coefficients on the lagged order flow variables for foreign investors and local institutions, implying that foreign investors' trading is persistent and potentially generates price pressures, as in Richards (2005).

From the coefficients on control variables, we find that QFII, HKC, and local institutional investors prefer to trade stocks with higher EP ratios and lower turnover. The time-series averages of adjusted R-squared in the first-stage cross-sectional regressions are 8.67%, 17.88%, 7.15%, and 6.82% for QFII, RQFII, HKC, and local institutions, respectively, suggesting that past returns, past flows, and firm-level characteristics explain a significant portion of foreign investors' trading in the cross-section.

We estimate a parallel specification to understand the holding preferences of foreign investors, where we link foreign investors' monthly holdings to 10 firm-level characteristics. Similar to equation (2), we first include past monthly returns, size, EP ratio, and turnover. In addition, following previous studies, such as Gompers and Metrick (2001) and Ferreira and Matos (2008), we include important firm characteristics related to their risk and profitability profiles, such as firm age (computed as the number of months since the stock was publicly listed), stock price level, dividend (computed as the cash dividends per share divided by stock prices at the end of the fiscal year), ROE (computed as the return on firm equity), volatility (computed as the variance of monthly returns over the previous 24 months) and leverage (computed as the total liability divided by total assets). Estimation results are reported in Table 3 Panel B. Consistent with the trading dynamics, foreign investors prefer to hold stocks with good past returns, large market capitalizations, and low turnover. In addition, they prefer stocks with low earnings-to-price ratios, high prices, long histories, high dividends, high profitability, low volatility, and low leverage. These findings are generally consistent with findings from previous studies.[10]

[Insert Table 3 here]

B. Predicting Stock Returns Using Foreign Order Flows

To investigate the return predictive power of foreign order flows in the cross-section as in Hypothesis 1, we also adopt the two-stage Fama-MacBeth (1973) regression method. We use the daily horizon as an example and extend to longer horizons. In the first stage, we estimate the following specification for each group *G* on each day *d*:

$$(3) \quad Ret(i,d) = c0(d,G) + c1(d,G)Oib(i,d-1,G) + c2(d,G)'Controls(i,d-1) + \epsilon(i,d,G).$$

The dependent variable $Ret(i,d)$ is the dividend and split-adjusted daily return for stock i on day d, which is expressed as a percentage. The primary independent variable is investor type G's order imbalance from the previous day, $Oib(i,d-1,G)$. For control variables, we follow the previous literature and include past stock returns and firm characteristics identical to those in equation (2). If a particular group *G* of foreign investors' order flow correctly predicts future stock returns, we expect a significantly positive $c1$. An insignificant $c1$ indicates no predictive power, and a significant and negative $c1$ implies that the foreign investors' trades are, on average, opposite to future stock price movements.

1. Predicting Next-day Return in the Cross Section

Table 4 Panel A presents the estimation results of equation (3). For QFII, the coefficient on Oib is 0.0649 (t-statistic=17.03), implying that QFII's order flow significantly and correctly

[10] Table IA1 of the Internet Appendix provides more detail on foreign investors' investment preferences regarding sectors. We find that the manufacturing sector has the largest holding and trading of foreign investors, while the education sector has the lowest holding and trading of foreign and local investors.

predicts future stock returns. In terms of magnitude, given the interquartile of QFII order flow is 1.8295, when we move from the 25th to the 75th percentile, the next day's return increases by 1.8295*0.0649*0.01=0.1188% (29.94% annualized).[11] In terms of RQFII and HKC, the coefficients on Oib are 0.0247 and 0.0783, both with significant *t*-statistics, corresponding to daily interquartile returns of 0.0305% and 0.0757% (7.69% and 19.08% annualized), respectively. These results support H1b or H1c, that, on average, all three types of foreign investors' order flows correctly predict the next day's stock returns with comparable interquartile returns.

We also examine whether the predictive power of foreign investors we document is comparable with that exhibited by local institutions. The coefficient on Oib for local institutions is 0.1330 (t-statistic=18.32), and the daily interquartile return is 0.0933% (23.51% annualized). Additionally, we compute the time series of the interquartile returns for each group of investors and compare whether their differences are significantly different from zero. That is, we multiply the time series of the estimated coefficients $\widehat{c1}(d, G)$ by investor G's interquartile range of order flow and obtain the time series of interquartile returns. At the bottom of Panel A, we report the average of the time-series interquartile return differences between different foreign investors and local institutions (the benchmark), with the *t*-statistics adjusted following Newey and West (1987) with five lags. The time-series average of the interquartile return difference between QFII and local institutions is 0.0255% per day (or 0.0255%*252day = 6.43% per year), with a *t*-statistic of 3.29. That is, the predictive power of the QFII order flows seems to be higher than that of the local institutions in terms of interquartile returns. The predictive power of RQFII and

[11] As an alternative to interquartile returns for measuring economic magnitudes, we also consider a standardized order imbalance measure. The results are similar and available on request.

HKC order flows is significantly lower than that of local institutions, with daily differences in interquartile returns being -0.0626% and -0.0184%, respectively. This simple comparison shows that QFII has the highest interquartile returns, local institutions are second, HKC is third, and RQFII is the lowest.

For the control variables, we find significantly negative coefficients on $Ret(d-6, d-2)$ and $Ret(d-27, d-7)$ in most specifications, suggesting strong reversal patterns in stock returns over the weekly and monthly horizons. In our sample period, while the size effect is insignificant, we find that stocks with high earnings-to-price ratios exhibit larger future returns, consistent with the value effect. The coefficients on turnover are most negative, consistent with the hypothesis that high trading volume might be driven by speculation and lower future lower returns. The average adjusted R^{2}'s from the first-stage OLS regressions ranges from 8.83% to 14.75%.[12]

[Insert Table 4 here]

2. Predicting Stock Returns over Longer Horizons

Given the strong one-day prediction for stock returns, we examine whether the predictive power remains over longer horizons. We modify the benchmark regression in equation (3) by using weekly returns, $Ret(i, w)$, as the dependent variable, with w ranging from 1 to 12. For instance, when w equals 1, $Ret(i, w)$ represents the cumulative stock return from $d+1$ to $d+5$; when w equals 2, $Ret(i, w)$ represents the cumulative return from $d+1$ to $d+10$, and so on. The independent variable and the control variables are the same as those in equation (3). Standard errors are adjusted following Newey and West (1987), with lag numbers equal to two

[12] In Figure IA1, we report the time series of estimated coefficients $\widehat{c1}(d, G)$ to ensure no outliers in the cross-sectional regressions over time. The time series is stable and does not display extreme values.

times the cumulative return days.[13] If foreign investors' predictive power extends to longer horizons, a positive and significant $c1$ is expected.

Table 4 Panel B presents the estimation results. To save space, we only report the coefficients on Oib and the implied interquartile cumulative returns. The statistical significance levels are denoted by asterisks, with ***, **, and * indicating significance at 1%, 5%, and 10%, respectively. Take QFII as an example; the coefficient for Oib is 0.1123 at week 1, and gradually increases to 0.2507 at week 12, with no sign of reversal. All coefficients differ from zero at the 1% significance level, indicating that order flows from QFIIs significantly predict returns over longer horizons, and possibly their return predictive power is related to long-term information, such as firm fundamentals, rather than short-term information, such as temporary price pressure. The patterns are similar for RQFII and local institutions. For HKC, the coefficient climbs from 0.0985 in week 1 to 0.1874 in week 8, then declines to 0.1677 in week 12, indicating a slight price reversal. Furthermore, from week 9 to week 12, the coefficients become insignificant, indicating that information in HKC order flows might not be as long-term as for QFII.

To compare the economic magnitude of the predictive power of various investors over longer horizons, we present the cumulative interquartile returns over the next 12 weeks at the bottom of Panel B. For a heuristic understanding of the magnitudes and trends, we also directly plot the interquartile return differences predicted by the order flows from different investors in Figure 3. We observe the following three patterns. First, all four lines generally trend up and do not present major reversals over 12 weeks (except for a slight flattening pattern for HKC order flows), suggesting that the predictive power of foreign and local institutions' order flows is

[13] We also calculate standard errors following Hansen and Hodrick (1980) and get similar results, which are available upon request.

lasting rather than transient. Second, the interquartile returns for QFII and local institutions are quite close to each other throughout the 12 weeks, and both are larger than those of RQFII and HKC. Our daily results in Table 4 Panel A show that QFII seems to have greater interquartile returns than local institutions over the next day. From the bottom of Table 4 Panel B, this advantage of QFII over local institutions remains over week 1 but becomes statistically insignificant. For the next 11 weeks, the performances of QFII and local institutions are similar and do not exhibit differences with statistical significance. That is, the predictive power of QFII and local institutions is comparable over the 12-week horizon. Third, RQFII and HKC have lower predictive power than QFII, and between the two, HKC has stronger predictive power than RQFII over week 1; but starting from week 2, RQFII performs better than HKC over the next 11 weeks. If we look across all three foreign capital channels, foreign investors' performance differences are related to their institutional background. As QFII has the strictest eligibility requirements, the tightest restrictions on capital flows over longer periods, and the widest investment scope, they may disproportionately be large international institutions focusing on long-term investments. RQFIIs face similar regulation settings to QFIIs, suggesting they may, too, largely be long-term investment institutions. However, RQFIIs may be somewhat less sophisticated because many are local institutions' Hong Kong subsidiaries whose primary goal is to absorb offshore RMB. For HKC, cross-border flows are much easier and less restricted, which may attract more short-term investors and lead to lower long-term return predictive power of order flows.

3. The Diversification and Liquidity Hypotheses

This section discusses the three alternative hypotheses regarding foreign investors' return predictability. The diversification hypothesis (H1a) indicates that if foreign investors mainly pursue diversification strategies, then foreign capital flows shouldn't predict local returns. Our finding that foreign investors strongly predict cross-sectional stock returns doesn't support Hypothesis H1a. In this section, we further examine whether foreign investors' predictive power is related to the stock's diversification benefit in the cross-section. Everything else equal, the foreign capital's predictive power might be weaker for firms with more diversification benefits because it's likely that foreign investors choose to invest in them for diversification benefits rather than other reasons.

Using monthly returns, we proxy the potential diversification benefits by the correlations between local stocks and the S&P 500 stock market index. Specifically, we compute the return correlations between stock i and the S&P 500 index using a rolling window of the previous 36 months with at least 24 non-missing observations. We define a dummy variable $HighDiv$, which is set to 1 if the correlation for stock i in month m is below the cross-sectional median, and 0 otherwise. Finally, we interact our order flow variable on day $d-1$ with the dummy variable in the previous month $m-1$ and estimate daily Fama-MacBeth regressions as shown in equation (4):

$$Ret(i,d) = c0(d,G) + c1(d,G)Oib(i,d-1,G) + c2(d,G)Oib(i,d-1,G) \times HighDiv(i,m-1) + c3(d,G)'Controls(i,d-1) + \epsilon(i,d,G). \tag{4}$$

If foreign investors have less predictive power for stocks with more diversification benefits, we expect $c2$ to be negative. Table 5 Panel A presents the results. We find that the estimated coefficients $\widehat{c2}$ are 0.0065, -0.0120, 0.0182, and 0.0046 for QFII, RQFII, HKC, and local institutions, respectively. These coefficients have mixed signs but are all insignificant, which doesn't support the diversification hypothesis.

Both the information hypothesis (H1b) and liquidity hypothesis (H1c) can be consistent with the strong and positive predictive power of foreign capital flows for future returns. Since our later discussions look further into the information hypothesis, we focus on the liquidity hypothesis in this section. The liquidity hypothesis has two parts. First, price pressure generated from persistent buy or sell orders can lead to positive predictive relations between order flows and future returns. Second, foreign investors' contrarian trading strategies provide liquidity to the market, and they might be rewarded for liquidity provision, which also implies a positive predictive relation. Both parts are consistent with our empirical findings in previous sections.

We rely on equation (2) to examine the liquidity hypothesis and follow Boehmer et al. (2021). We decompose the foreign order flows into multiple components related to contrarian, persistence, and others. The contrarian component is calculated as the estimated coefficient $\widehat{a1}(d, G)$ times $Ret(i, d-1)$,[14] the persistence component is calculated as the estimated coefficient $\widehat{a4}(d, G)$ times $Oib(i, d-1, G)$, and the residual component is the intercept plus the regression residual $\hat{\epsilon}(i, d, G)$. Then, we re-estimate equation (3) to assess the return predictive power of each of the above components. If foreign investors' return predictive power comes from contrarian trading (liquidity provision), we expect significantly positive coefficients on the order flow components related to the contrarian component. Similarly, if foreign investors' return predictive power comes from order persistence, we expect significantly positive coefficients on the order flow components related to the persistence component.

[14] In the case of RQFII, HKC, and local institutions, because contrarian patterns only appear for the previous day's return, we only use the previous day's return and the estimated coefficient $\widehat{a1}$. For QFII, contrarian patterns exist for the previous day, the previous week, and the previous month, so we include all these previous returns and the estimated coefficients $\widehat{a1}$, $\widehat{a2}$, and $\widehat{a3}$.

Table 5 Panel B presents the decomposition results. The coefficient on the order flow variables related to contrarian trading for QFII is 0.3367, significantly different from zero, and the daily interquartile return for contrarian trading is 0.0475%, suggesting that liquidity provision contributes to the positive predictive relation between QFII flow and future return. However, the coefficients on contrarian components are -1.3243, -0.9796. and 0.0184 for RQFII, HKC, and local institutions, and none is statistically significant, implying that liquidity provision might not be important for their return predictability. For the price pressure hypothesis, we find that the persistence component has positive and significant coefficients for QFII and local institutions with daily interquartile returns of 0.1286% and 0.0861%, respectively, but it is not significant for RQFII or HKC. That is, we find mixed evidence for the liquidity provision and price pressure story.[15] Finally, the residual order flow component always positively and significantly predicts future stock returns, with daily interquartile returns of 0.1048%, 0.0271%, 0.0726%, and 0.0780% for QFII, RQFII, HKC, and local institutions, respectively, implying that a significant portion of foreign investors' return predictive power might not be related to price pressure or liquidity provision.

[Insert Table 5 here]

Overall, our results suggest that price pressure and contrarian trading from foreign investors might not be the main reasons for foreign investors' return prediction capacity. Our hypothesis H1b suggests that information might be behind the positive predictive relation between foreign order flows and local returns, which we investigate in Section IV.C.

[15] We also test the H1c hypothesis by decomposing the order flow variable into persistent and temporary components, as suggested in Richards (2005). The empirical results show that the temporary component (representing the day-to-day fluctuations in order flows), rather than the persistent component (representing the 20-day moving average in order flows), is the main reason for foreign investors' predictive power for future returns. These results are available on request.

4. Foreign Order Flows vs. Local Order Flows

Our results thus far show that foreign investors, such as QFII, perform similarly to local institutions. Foreign and local investors may share overlapping information so that they trade similarly, leading to similar predictive patterns. They may also possess different information and display similar magnitudes of predictive power by coincidence. To find out whether the information is mostly overlapping or largely unique among different groups of investors, we orthogonalize each group's order flow with respect to another group's order flow and examine the residual's predictive power for future returns. For instance, for each day *d*, we project foreign investors' order flows onto local institutions' order flows as follows,

$$Oib\left(i,d,G_{Foreign}\right) = e0(d,G) + e1(d,G)Oib(i,d,G_{Local}) + \epsilon(i,d,G). \tag{5}$$

We follow the previous literature (e.g., Kelly and Tetlock, 2013) and drop missing observations in equation (5) in the regressions. After we obtain the time series of $\widehat{e1}(d,G)$, we decompose the foreign order flow into two parts,

$$Oib^{overlap}_{i,d,G_{Foreign}} = \widehat{e1}(d,G)Oib(i,d,G_{Local}), \tag{6}$$

$$Oib^{specific}_{i,d,G_{Foreign}} = \widehat{e0}(d,G) + \hat{\epsilon}(i,d,G),$$

with the first term being the overlapping component with local institutions and the second term being the foreign-specific component. After the decomposition, we re-estimate equation (3) by including both components. Similar procedures are followed to decompose local institutions' order imbalance with respect to order flows from all three foreign investor groups.

Table 6 Panel A reports the estimation results. For QFII, the coefficients on $Oib^{overlap}_{Foreign}$ and $Oib^{specific}_{Foreign}$ are 0.3553 and 0.0593, with *t*-statistics of 0.18 and 15.67, respectively, indicating that QFII's predictive power primarily stems from foreign-specific information rather than from the overlapping component with the local institutional order flows. In terms of economic magnitude, the daily interquartile returns for overlapping and foreign-specific order flows are 0.0399% and 0.1034%, respectively, indicating that the foreign-specific information in order flow contributes more to QFII's predictive power. Similar patterns are observed for RQFII and HKC, in that only the foreign-specific order imbalance displays significant return predictive power. In contrast, the pattern differs for local institutions, where the overlapping and local-specific components of order flows significantly predict future stock returns. In terms of economic magnitude, the interquartile return for the overlapping component is 0.0769%, somewhat smaller than the interquartile return of 0.1205% driven by the local-specific order flows.[16] If we combine these two components, the overall interquartile return is 0.1433% = (0.0399%+0.1034%).

[Insert Table 6 here]

Alternatively, we also directly include both foreign capital flow and local foreign capital flow together, without orthogonalization, to assess the "incremental" predictive power of foreign capital flows in the existence of local flows. The results are reported in Panel B of Table 6. All coefficients, foreign or local, are positive and significant, suggesting strong predictive power for return from all foreign and local capital flows. Compared with those in Table 4 Panel A, the magnitudes of the coefficients are slightly smaller. For instance, the coefficient for QFII is 0.0649 in Table 4 and 0.0593 in Table 6 Panel B, both highly significant. These results suggest

[16] If we put these two components for QFII together, the overall interquartile return is 0.1433% (= 0.0399%+0.1034%) and is comparable but larger than 0.1188% in Table 4. The overall interquartile return for local institutions is 0.1974% (=0.0769%+0.1205%), significantly larger than 0.0933% in Table4. We want to warn readers that these numbers are not directly comparable for two reasons: sample size and estimation procedure. The sample for QFII estimation has 780,128 observations, similar to those in Table 4. However, the sample for the local institution has only 104,111 observations because it needs data from RQFII, which has many missing observations. Also, the estimation in Table 4 is a standard two-stage Fama-MacBeth regression using raw foreign capital data. In contrast, the estimation in Table 6 has one more orthogonalization before the Fama-MacBeth regression, which separates raw data into two components.

that all foreign capital flow variables have significant "incremental" predictive power for future returns, in the presence of a local capital flow variable.

Our finding that foreign-specific order flows contribute more to foreign investors' return predictive power, especially for QFII, implies that foreign investors may possess unique informational advantages or have superior information-processing abilities in the local market. The results are also consistent with our previous findings that information may be a major reason for the return predictive power of foreign order flows. Next, we examine the information contained in the foreign order flows.

C. Firm-Level Information and Return Predictive Power

1. Foreign Order Flows and Earnings Announcements

In this section, we formally test the H2 hypothesis by examining whether foreign investors can predict firm-level news, using stock returns around these days. We separate firm-level news into pre-scheduled and unscheduled events. Our study includes firms' earnings announcements as pre-scheduled events because publicly listed firms in China must disclose the earnings announcement dates on official websites designated by the regulator (CSRC). In contrast, analyst-related announcements and media news are considered unscheduled events.

We obtain earnings announcement data from WIND. Our sample includes 15,477 earnings announcements, accounting for 1.52% of all stock days in our sample. To investigate whether foreign investors process information on earnings announcements, we examine whether the order imbalance of foreign investors from the previous trading day predicts earnings news on the next day. The earnings news is computed using cumulative abnormal returns (CAR) over different horizons, by subtracting the same period market returns. Given that earnings are announced quarterly, and earnings news is not evenly distributed over calendar days, we modify the daily Fama-MacBeth setup to a quarterly horizon, where we first estimate the cross-sectional regression for each quarter q,

$$CAR(i,d,d+k) = f0(q,G) + f1(q,G)Oib(i,d-1,G) + f2(q,G)'Controls(i,d-1) + \epsilon(i,d,G). \tag{7}$$

All controls are the same as in equation (3). After we obtain the quarterly coefficients, we calculate the time-series average and conduct inferences accordingly. If coefficient $f1$ is significantly positive, it implies that the previous day's order imbalance predicts the future earnings news correctly, which would support H2.

Table 7 Panel A presents the estimation results for equation (7). For the abnormal return on the event day 0, AR[0], the coefficient for QFII Oib is 0.0947, with a significant *t*-statistic of 2.61, suggesting that the previous day's QFII order flows predict earnings news positively and significantly. When we extend the horizon to two days using CAR[0,1], one quarter using CAR[0,61], and one year CAR[0,251], the corresponding coefficients are all significantly positive and the interquartile returns gradually increase to 0.5430%. We find similar but weaker results for RQFIIs and HKC investors. These results provide direct evidence that order flows from foreign investors contain information about firm earnings, which support H2. The local institutions in the last column display similar predictive patterns to those of QFIIs, but with larger magnitudes for longer horizons, indicating that local institutions might be better informed of local firms' earnings news in the long run.

[Insert Table 7 here]

2. Foreign Order Flows, Analyst-related Events, and Financial Media News

Besides scheduled earnings announcements, we examine whether foreign investors have an informational advantage for unscheduled news, such as analyst-related events and media reports. For analyst data, though CSMAR is a widely used analyst database (Dong, Fisman, Wang, and Xu (2021), and Chen, Ma, Martin, and Michaely (2022)), its coverage is incomplete, particularly in earlier periods. Following literature (e.g., Jia, Wang, and Xiong (2017), and Li, Wong, and Yu (2020)), we construct a comprehensive analyst sample from four major data providers: CSMAR, WIND, RESSET, and SUNTIME. Focusing on forecast revisions and recommendation changes. Our sample includes 41,722 analyst-related events, accounting for 4.09% of all stock days in our sample.[17] For financial media news, which is shown to be important in previous literature such as Tetlock, Saar-Tsechansky, and Macskassy (2008), we collect financial media news data from the Chinese Research Data Service Platform's Financial News Database (CFND), following Ge and Zhang (2022). CFND gathers financial news from over 400 websites and 600 newspapers, including reports from the largest mainstream online financial media outlets, all written in Chinese. Our sample contains 353,551 media news days, accounting for 34.69% of total observations.

To investigate how foreign investors' return predictive power relates to analyst-related and financial media news, we re-estimate the quarterly Fama-MacBeth regression as in equation (7) but use the cumulative abnormal returns around analyst reports or financial media news release dates. If foreign investors are informed, we expect significant and positive coefficients on the previous day's order flow.

Table 7 Panel B presents results for analyst-related events. Take QFII as an example. We find foreign investors can predict abnormal returns on analyst report release days, with a coefficient of 0.0746 and a *t*-statistic of 3.33. The significant return predictive power can extend to one year CAR[0,251], with a coefficient on order flows of 0.5705 and a *t*-statistic of 2.59.

[17] The dataset construction details are provided in the Internet Appendix IA.I.

Panel C presents the estimation results for media news. Similarly, the coefficients on order flows are 0.0789 and 0.5475 for AR[0] and CAR[0,251], with *t*-statistic of 5.83 and 6.30. Similar patterns hold for RQFII and HKC investors. Overall, these results imply that foreign investors' order flows contain information about analyst-related activities and media news, which also supports H2.[18,19]

We are curious how foreign investors overcome potential informational disadvantages and present strong predictive power for future firm-level news. From anecdotal evidence, we find that many foreign institutions establish offices near Mainland China, like Hong Kong, to narrow information asymmetry induced by geographical distance. In fact, according to SAFE (State Administration of Foreign Exchange), around 25% of QFIIs and 43% of RQFIIs are located in Hong Kong. Meanwhile, many foreign institutions hire managers of Chinese ethnicity or with significant Chinese working experience to overcome cultural and regulatory barriers. For instance, J.P. Morgan asks research associates for China-related roles to obtain "all necessary CSRC licenses"; BlackRock searches for VPs for equity research with "5-10 years China equity market experience, preferably in leading financial institutions"; and Goldman Sachs directly asks for "strong communication skills in Chinese (written and verbal)".

[18] If foreign investors are informed about future price movements, we suspect that their predictive power would be stronger for big-news days. Motivated by Jiang and Zhu (2017), we define big news days as stock returns that fall outside of the 5th and 95th percentiles of all event-day returns in the prior quarter, and the remaining news days are categorized as non-big news days. Big news days can be associated with the most value-relevant firm events, which cause significant movements in stock prices. We examine this hypothesis in Internet Appendix IA.II and Table IA2 and find that foreign investors better predict stock returns on big news days. A decomposition methodology following Boehmer, Jones, Wu, and Zhang (2020) also show that big news days have large contribution to investors' overall performance.

[19] We conduct robustness checks using multiple alternative specifications for firm-level news, such as including firm event dummy variables, separating positive and negative news, etc. Our main results are robust in these specifications in the Internet Appendix Table IA3.

D. Information Environment

In this section, we investigate whether improvements in the information environment contributes to foreign investors' return predictive power, as suggested by H3. When information becomes more accessible to foreign investors, foreign investors with skills and resources may face lower information barriers, and they may be able to better predict future stock returns.

Chinese firms are important participants in the global supply chain as suppliers. Further, consumers and foreign investors may be more familiar with the fundamentals of firms that conduct significant cross-border business activities. Comparatively speaking, the information environment is better, from the perspective of foreign investors, for firms with more overseas activities. We define the variable $Overseas$ as the absolute value of the ratio of overseas income to overall revenue. We then investigate the relation between foreign investors and firms engaged in cross-border business in two steps. First, we use Fama-MacBeth regressions, similar to equation (2), to investigate how foreign investors' stock holdings relates to firms' exposure to overseas business, with foreign holding in month m is the dependent variable and $Overseas$ is the key independent variable. A positive coefficient on $Overseas$ suggests that firms with higher overseas revenue attract more foreign investors. Second, we use daily Fama-MacBeth regressions as shown in equation (4) to investigate how overseas business relates to foreign investors' return predictive power, replacing $HighDiv$ with $Overseas$. A positive coefficient on the interaction term indicates that foreign investors better predict stock returns for firms with a higher proportion of overseas income.

Table 8 Panel A presents the estimation results for firms with overseas business. For foreign holdings, we find that the coefficients of $Overseas$ are 0.0015, -0.0005, 0.0007 and 0.0107 for QFII, RQFII, HKC and local institutions, respectively. Only the coefficients for QFII and local institutions are statistically positive, indicating that enterprises with an intense exposure to international business have a high level of ownership by QFII. In terms of the return prediction, the coefficients on the interaction are positive, ranging between 0.0261 and 0.0690, with statistical significance for QFII and HKC at the 95% confidence level. The results show that the predictive power of foreign order flows is stronger for firms with greater levels of overseas activities. Our results are also consistent with findings in Wang, Yu, and Zhang (2023), which show that the presence of foreign investors with informational advantages significantly reduces the firms' information management behavior related to overseas operation events, which become much difficult to access by domestic investors following Google's unexpected withdrawal from mainland China in 2010.

Bae, Bailey, and Mao (2006) and Harford et al. (2019) demonstrate that analysts make efforts to produce information, and high analyst coverage should improve the transparency of corporate information. Following the literature, we use analyst coverage to assess the information environment, where $Coverage$ is the logarithm of one plus the number of analysts. We repeat the two-step analysis and present results in Table 8 Panel B. For foreign holdings, we find positive and significant coefficients on $Coverage$ for both foreign investors and local institutions, meaning that firms with high analyst coverage have high foreign ownership. In terms of return prediction, the coefficients on the interaction between Oib and $Coverage$ are all positive, implying that investors' return predictive power is higher for stocks with higher analyst coverage or a better information environment. However, the coefficients on the interaction terms are significant for HKC and local institutions but not for QFII or RQFII. Our findings suggest that improvement in the information environment might contribute to foreign investors' predictive power on cross-sectional stock returns, supporting hypothesis H3.

Finally, we consider the top shareholder holdings as another candidate metric of the information environment. Fan and Wong (2002) demonstrate that concentrated ownership imply poor minority shareholder protection, resulting in agency conflicts between major shareholders and outside investors, low trust in earnings information, and severe information asymmetry. We define $TopHolding$ as the top shareholder's holding shares divided by the total outstanding, with lower top shareholder ownership indicating better firm-level information. Table 8 Panel C shows the results. For foreign holdings, the coefficients on $TopHolding$ are negative for all foreign investors, but significant for QFII, HKC, and domestic institutions. This indicates that firms with lower ownership from the top shareholder attract higher foreign investors' holdings. In terms of return prediction, for QFII, the coefficient on the interaction between $TopHolding$ and the previous day's order flow is -0.0422, with a t-statistic of -2.31, meaning that foreign investors exhibit stronger return predictive power on stocks with lower ownership from the top shareholder. The pattern does not hold for RQFII and HKC. Our findings support hypothesis H3 that foreign investors, QFII in particular, exhibit elevated return predictive power under a better information environment.

Overall, we provide suggestive evidence that improvements in the information environment may compensate for foreign investors' disadvantages in the local market and lead to comparable performance between foreign and local institutions regarding firm-level return prediction.[20]

[20] We also examine the relation between foreign investors' return predictive power and noise trading. Jones, Shi, Zhang, and Zhang (2025) find that Chinese retail investors who have average account sizes in the past 12 months of less than 3 million CNY do not correctly predict local stock returns in both short and long periods, suggesting that they are possibly noise traders in the Chinese A-share Market. Motivated by their findings, we use small retail traders' trading volumes (RT1-RT3 in Jones et al. (2025)) as a proxy for noise trading. We find positive coefficient on the interaction term for QFII with a t-statistic of 1.41, but negative values for other investors. The mixed results may be that while informed investors can be compensated by engaging in costly information acquisition (Grossman

[Insert Table 8 here]

V. Further Discussion and Robustness

A. The China Setting

In this section, we turn to the question of what specific factors contribute to foreign investors' return predictive power in China instead of other emerging markets. Extant research indicates that information asymmetry may explain the performance differences of foreign investors across markets. Classic theory (Grossman and Stiglitz,1980) suggests that investors expend resources to become informed only when the expected benefits outweigh these costs. The ingredients describing this tradeoff vary significantly across both markets and time; hence, the mixed outcomes across the academic literature may underscore the fact that the benefits of costly information acquisition hinge on market conditions.

In the spirit, China's market evolution has likely altered the cost-benefit tradeoff of gathering firm-specific information for foreign investors. In earlier decades, foreign institutions often faced prohibitively high information costs, from language barriers and scarce, reliable data to limited on-the-ground research access, potentially deterring deep firm-level analysis. More recently, the growth of financial databases, improved analyst coverage of Chinese firms, and better corporate governance have lowered information-gathering costs. In essence, the Chinese market may now offer an environment where the *expected cost* of being informed is low relative to the *expected benefit*, potentially incentivizing global investors to establish local research teams, invest in data analytics, and develop expertise on Chinese stocks.

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and Stiglitz,1980), noise traders can drive prices persistently away from fundamental values, engendering risks for rational arbitrageurs (e.g., De Long, Shleifer, Summers, and Waldmann (1990)). The results are available on request.

To gauge this possibility, we rely on the existing literature for proxies of the information environment. Bae et al. (2006) demonstrate that a high degree of market openness to foreign equity investors is associated with transparency. Ferreira et al. (2017) suggest that foreign investors have low predictive powers in markets characterized by weak shareholder protection and opaque financial disclosure. Therefore, we collect the prevalence of foreign ownership index from the World Economic Forum, the shareholder rights index from the World Bank, and the strength of auditing and accounting standards index as three market-level proxies.[21] We present the time series of these variables for China and the average of emerging markets in Figure 4.

The figure clearly shows two patterns. First, the overall quality of the Chinese information environment is below the average emerging market. Second, there is a gradual improvement in these proxies over the years. In fact, we conduct a time-series trend test in Table 9 Panel A, and document significant and positive trends in the prevalence of foreign ownership and shareholder rights. Given these positive trends in improvements of the information environment, the cost-benefit tradeoff may now tilt towards foreign institutional investors acquiring and trading on cost information in China. As discussed above, we provide firm-level evidence within China in Section IV.D. The results suggest that an improved information environment, using several proxies, is associated with increased foreign ownership and greater return predictive power from foreign investors.

While exploratory, our analysis suggests that the informed returns of foreign investors in China that we document may be rooted in traditional economic mechanisms – lower information costs, better governance, and liberalized access, consistent with information-theoretic expectations. We do not assert that foreigners will consistently outperform locals;

[21] Internet Appendix Table IA4 presents definitions of these market-level indicators.

instead, we highlight how changes in the informational landscape have empowered foreign investors in the recent period examined. Looking ahead, this advantage may evolve as market conditions change. As more foreign and domestic institutions become informed and competition intensifies, the excess returns to any one group's information advantage should diminish.

[Insert Table 9 here]

B. Regulation Changes

China gradually relaxed regulations on foreign investors during our sample period. These reforms mainly focus on three aspects: extending access to international investors, boosting quotas or removing position limitations for foreign investments, and relaxing the requirements of lock-up periods. On the one hand, fewer restrictions on foreign capital may lower the potential cost of foreign investment and attract more sophisticated overseas investors, thereby enhancing foreign investors' overall return prediction capacity. On the other hand, it is also likely that when a quota increases, foreign investors' portfolios may become less profitable as they turn to less compelling strategies, lowering their overall predictive power. According to Bae et al. (2006), increased market liberalization is associated with a better information environment; we expect that foreign capital flows' predictive power for returns is higher when regulation is friendlier towards foreign investors.[22]

To examine the hypothesis, we regress the time series of estimated coefficients $\widehat{c1}(d, G)$ from equation (3) on a series of regulation dummies as in equation (8),

$$\widehat{c1}(d, G) = r0(G) + r1(G)'Regulations(d-1) + \epsilon(d, G). \tag{8}$$

[22] Take QFII as an example, regulators increased the investment quota in February 2016 and January 2019, removed the investment constraint in September 2016, and relaxed the requirement of lock-up period and limits of capital repatriation in 2018. Please refer to the Internet Appendix IA.III for details.

If the hypothesis is true, foreign investors' predictive power increases after a particular regulation change, implying positive values of the coefficient vector $r1(G)'$. In Table 9 Panel B, we find no significant relation between policy relaxation and QFII/RQFII return predictive power. Interestingly, the coefficients on regulation dummies for HKC are positive and significant, indicating that HKC has more cross-sectional predictive power following investment quota extension. These results indicate that quota relaxation effectively boosts foreign capital flows' predictive power. However, we acknowledge that it is quite difficult to convincingly link return predictability in one time period to the degree of market liberalization, especially when a host of things can change over time.

C. Counterparties

China remains a retail-dominated market, and it is important to understand against whom foreign investors trade in China: local retail investors or local institutions. Given findings in Jones et al. (2025) that smaller retail investors' trading activity *negatively* predicts future stock returns, it is interesting to examine whether foreign investors disproportionately trade against local retail investors. To answer this question, we separate counterparties into foreign investors, local institutions, and retail investors (RT). Next, based on the daily order imbalance measure, we separate investor groups' daily trade directions into buy (B) and sell (S). With the three groups of investors and the two sides of each trade, all stock-day observations are separated into six bins: BBS, SSB, BSS, SBB, BSB, and SBS, with the first letter indicating the trade direction of foreign investors, the second for local institutions, and the third for retail investors. Take QFII as an example. QFII trades mostly line up with the local institutions (53% of the time), and mostly against local retail investors (61% of the time). Similar patterns hold for RQFII and HKC.

To examine whether foreign investors' return predictive patterns change with different counterparties, we estimate daily Fama-MacBeth regressions as shown in equation (9):

$$Ret(i,d) = a0(d,G) + [\sum_{k=1}^{6} \mathrm{c1}(k,d,G) * I(k,d,G)]Oib(i,d-1,G) + \mathrm{c2}(d,G)'Controls(i,d-1) + \epsilon(i,d,G). \quad (9)$$

The indicator variable $I(k,d,G)$ is equal to one if trading from foreign investor group G for stock i on day d-1 falls in the k-th counterparty bin, otherwise, it is zero. Table 9 Panel C presents the estimation results. Take QFII as an example. When they trade on the same side with local institutions and on the opposite side of local retail investors, as in the bins of BBS and SSB, the coefficients are positive and significant, indicating that both foreign and local institutions have an informational advantage over local retail investors. There are also cases when foreign investors trade differently from local institutions, but they still significantly and positively predict future returns, as in SBB and SBS. The results are consistent with our main findings that foreign investors may possess specific informational advantages in the local market relative to local institutions. Similar patterns also hold for RQFII and HKC.

D. Account Performance of Foreign Investors

Does the significant predictive power of foreign order flows lead to strong investment performances? We define the total cash flows for foreign investor groups as the sum of the capital gain from holdings plus trading proceeds minus transaction costs. Following Barber, Lee, Liu, and Odean (2009), we further decompose the total cash flow into stock selection, market timing, and transaction costs. Intuitively, the stock selection component captures whether investors can perform better by actively selecting stocks that outperform the stock market. The market timing component captures whether the investors can strategically make investment decisions based on the relative performance between the stock market portfolio and the risk-free asset, and, thus, time the market. Finally, we add all the daily gains from the sample and compute the annual performance. To understand the return percentage of investment, we divide the account gains by the aggregate holding values from the previous period and compute the annualized statistics. To save space, we present the details in the Internet Appendix IA.IV.

Table 9 Panel D presents the results. The annual gains for QFII, RQFII, HKC, and local institutions are 40.48, 11.97, 60.62, and 376.58 billion RMB, respectively. The annual returns for QFII, RQFII, HKC, and local institutions are 17.79%, 20.81%, 17.73%, and 10.22%, respectively, suggesting notable return performance in each case. In terms of the decomposition, the stock selection component accounts for the majority of realized investor performance. In contrast, the market timing performance component is all negative, suggesting that all these investors might have better skills in stock selection than market timing. These findings are consistent with earlier studies, such as Barber et al. (2009) and Jones et al (2025).[23]

E. Robustness Checks

We perform multiple robustness tests to ensure our results are not sensitive to data treatments. In the main results, we do not include observations in the regressions with missing order flow values. In this case, one may be concerned about comparability issues if the number of observations differs across investor groups. Here, we consider several alternatives. First, we require non-missing order flows from foreign and local investors at the stock-day level, leaving us with 104,111 observations. Then, we estimate one-day and long-term return prediction

[23] Readers might find that the annualized return for QFII (17.79%) is lower than that of RQFII (20.81%), inconsistent with the findings in Table 4. Notice that the results are not directly comparable because Table 4 only considers trading, while Table 9 Panel D considers trading and holding. In Internet Appendix Table IA5, we decompose total performance into holdings, trading, and transaction costs. RQFII's performance mostly comes from holding, not trading, and the trading gain is much smaller than that of QFII, consistent with our results in Table 4. We would also like to point out that the total stock capitalization held by RQFII is significantly smaller than that of QFII investors, which boosts RQFII's gains from previous stock holdings. For instance, Table 2 Panel A shows that the average daily stock holdings for QFII and RQFII are 240 and 58 billion CNY, respectively.

regressions as in equation (3) and present results in Table 10 Panel A and B, respectively. We find that foreign order flows still significantly predict local stock returns over short and long periods, consistent with findings in Table 4.

Second, we replace missing order flow variables with zeros and estimate one-day return prediction regressions. In Panel C, we find positive and significant coefficients on order flows for foreign and local investors, meaning that foreign investors predict local stock returns. However, owing to smaller interquartile ranges with zero order flows, the interquartile returns are lower than the figures in Table 4 Panel A.

One concern regarding Chinese trading data is that price limits are constantly met, accounting for 1.71% of total observations in the sample. To ensure our results are robust, we remove all stock-day observations when price limits are hit on *d-1* and re-estimate the daily return predictive regressions. Results in Panel D show that foreign order flows still have significant return predictive power for stock daily returns when stock prices don't hit price limits. For instance, the coefficient on Oib for QFII is 0.0707 with a *t*-statistic of 18.88.

To test the robustness of our results for an alternative estimation timeline, we skip day *d* and examine whether foreign investors' order flows on day *d-1* predict stock returns on day *d+1*. From the results in Panel E, the coefficients on order flows are 0.0399, 0.0181, 0.0414, and 0.1043 for QFII, RQFII, HKC, and local institutions, respectively, and all are statistically significant.

In Table 6, we compare the prediction of foreign and local investors by orthogonalization and by including local capital flows as control. Here, we conduct a horse race estimation by including order imbalances from all four investor groups in one regression to predict the next day's return. One caveat of this approach is that all order flow variables need to have a non-missing value for the stock on that day, a restriction that then excludes more than 90% of our sample. Results in Panel F show positive and significant coefficients on order flows from QFII, RQFII, and HKC investors, implying that foreign investors have “incremental” return predictive power relative to local institutions. Overall, we still find that foreign investors have significant return predictive power on local stocks across these four robustness tests.

[Insert Table 10 here]

VI. Conclusion

Using a comprehensive proprietary dataset, we investigate whether foreign order flows predict cross-sectional stock returns. We find that foreign investors predict future stock price movements over both short and longer horizons, and the magnitude is comparable across foreign and local institutions. When relating their predictive power to firm-level information, foreign investors successfully predict firm-level earnings, analyst, and media news. Contrary to most previous studies, the evidence suggests that foreign investors are not at an informational disadvantage and have some ability to process firm-level information. Finally, to explain how foreign investors process local firm-level news, we show that improvements in the information environment, investment in firms with cross-border business activities, and stock market liberalizations can facilitate foreign investors’ return predictability in the cross-section.

These findings have important implications for policymakers and researchers. Regulators should promote the development of price discovery and financial market efficiency by examining how to take advantage of foreign investors’ relative abilities.

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Table 1 Comparison of QFII, RQFII, and HKC

	QFII	RQFII	HKC
Investor	1.Institutional investors such as security companies, commercial banks, asset management companies and others 2. Requirements on the scale of assets under management and operational periods.	1.In 2011, only Hong Kong subsidiaries of Chinese financial institutions 2.gradually extended to other locations.	Hong Kong and overseas investors, including both retail and institutional investors.
Capital Control	1. 3-month lockdown period for non-open-end funds. 2. The monthly remittance of capital and profits could not exceed 20% of total assets at the end of previous year 3. Restrictions were removed on June 10, 2018	3-month lockdown period for non-open-end funds, which was removed on June 11, 2018.	Not required
Investment Quota	1. Basic quota for a single QFII was limited by the scale of assets under management and was no more than $5 billion 2. Aggregate QFII quota was raised to $300 billion on January 14, 2019 3. Restriction cancelled on September 10, 2019.	1. Basic quota for a single RQFII was limited by the scale of assets under management 2. Aggregated RQFII quota varies for different locations. For example, the aggregate quota for Hong Kong was RMB 500 billion on July 4, 2017 3. Restriction cancelled on September 10, 2019.	1. Total investment quota was set at RMB 300 billion. Restriction cancelled on Aug 17, 2016. 2. Initial northbound daily quota was RMB 13 billion and rose to 52 billion after May 1, 2018.
Funding	1.Remit foreign currency as the principal 2.Both FX and RMB are allowed after May 7, 2020.	1.Offshore Chinese Yuan as the principal 2.Both FX and RMB are allowed after May 7, 2020.	Not required
Investable Stock	1. All A-share stocks. 2. Fixed income and other financial products.	1. All A-share stocks. 2. Fixed income and other financial products.	1.Constituent stocks of some specific stock indices. 2.A shares with H shares listed on the Hong Kong Stock Exchange.
Ownership	1. A single QFII licensee or RQFII licensee or HKC cannot hold more than 10% of a given company's A-shares. 2. Total A shares held by all QFII, RQFII and HKC investors for any given company cannot exceed 30% of its total outstanding shares.		

Table 2 Summary statistics of foreign investors and local institutions

This table summarizes trading and holdings by foreign investors and local institutions. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. Foreign investors refer to Qualified Foreign Institutional Investors (QFII), Renminbi Qualified Foreign Institutional Investors (RQFII), and investors via the Hong Kong Connected Scheme (HKC). We refer to local mutual funds, hedge funds, insurance companies, security companies, and other institutional investors as local institutions (Local INST). In Panel A, we report the daily average number of stocks held and traded by investors, the daily average of investors' aggregated trading volume (the mean of buy and sell) in billion RMB, and the daily average of investors' aggregated holdings in billion RMB. At the stock-day level, the investors' order imbalance measure (*Oib*) is defined as buy volume (in shares) minus sell volume (in shares) divided by the sum of buy and sell, as shown in equation (1). Panel B reports the time-series average of the cross-sectional mean and standard deviation. *AR(1)* is the cross-sectional mean of the first-order autocorrelation of the order imbalance measure. We also report the time-series average of the cross-correlations of the order imbalance measure across QFII, RQFII, and HKC.

Panel A. Time-series average of investors' aggregate trading and holdings

	QFII	RQFII	HKC	Local INST
Daily trading volume (Bil. RMB)	1.51	0.16	4.33	28.95
Trading volume of total market (%)	0.79%	0.08%	2.24%	14.80%
Number of stocks traded	946	174	561	1,227
Daily Holding (Bil. RMB)	240.23	58.01	311.14	3590.2
Holding shares of total market (%)	0.95%	0.23%	1.20%	14.19%
Number of stocks held	1,261	901	744	1,297

Panel B. Time-series average of cross-sectional statistics of the order imbalance measure

				Correlations		
	Mean	Std	AR(1)	Oib(QFII)	Oib(RQFII)	Oib(HKC)
Oib(QFII)	-0.01	0.86	0.09			
Oib(RQFII)	0.02	0.82	0.44	0.09		
Oib(HKC)	0.02	0.58	0.12	0.14	0.04	
Oib(Local INST)	-0.01	0.47	0.18	0.09	0.06	0.06

Table 3 Understanding Foreign Investors' Trading and Holding

This table presents estimation results on what affects foreign investors' order flows and stock ownership. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month. In Panel A, we estimate daily Fama-MacBeth (1973) regressions as in equation (2). The dependent variable *Oib* is the order imbalance for stock *i* on day *d*. The key independent variable is the previous day's stock return *Ret(i,d-1)*. For control variables, we include the previous weekly cumulative return *Ret(i,d-6,d-2)*, the previous monthly cumulative return Ret*(i,d-27,d-7)*, log firm size (*Lnsize*) from the previous month-end, firm earnings to price ratio (*EP*) as the ratio of most recently reported quarterly earnings to the market capitalization from the previous month-end, and turnover (*Turnover*) as the ratio of monthly trading volume to floating A shares from the previous month-end. In Panel B, we estimate monthly Fama-MacBeth (1973) regressions as follows,

$$IO(i,m,G) = b0(m,G) + b1(m,G)Ret(i,m-3,m-1) + b2(m,G)Ret(i,m-12,m-4) + b3(m,G)'Controls(i,m-1) + \epsilon(i,m,G).$$

The dependent variable *IO* is calculated as investors' holding shares divided by total outstanding floating shares. *Ret(i,m-3,m-1)* is the past three-month gross return. *Ret(i,m-12,m-4)* is the nine-month gross return preceding the month *m-3*. *Volatility* is the variance of monthly returns over the previous 24 months. *Price* is the stock price per share. *Dividend* is the cash dividends per share divided by stock prices at the end of fiscal year. *Age* is the number of months since the stock was publicly listed. *Leverage* is the total liability divided by total assets. *ROE* is the return on firm equity. We use the natural log for firm size, stock price and firm age in regressions. *Adj-*R^2 is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. We adjust standard errors using Newey-West (1987) to account for potential serial correlations in the coefficients with five lags. To spare the space, we omit the intercept in the regression. We report *t*-statistics in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Trading

Dep: Oib(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Ret(d-1)	-4.6313***	-0.7709*	-2.1991***	-1.8838***
	(-28.51)	(-1.78)	(-16.24)	(-22.58)
Ret(d-6,d-2)	-0.2730***	0.4295**	0.2293***	0.0233
	(-4.53)	(2.50)	(5.48)	(0.70)
Ret(d-27, d-7)	-0.1218***	0.2384***	0.0418**	-0.0103
	(-4.12)	(2.62)	(2.04)	(-1.15)
Oib(d-1)	0.1299***	0.2349***	0.1346***	0.2086***
	(19.61)	(23.17)	(21.14)	(56.21)
Lnsize	0.0042	-0.0001	0.0051	-0.0047***
	(0.82)	(-0.01)	(1.35)	(-2.82)
EP	0.7800***	-0.3007	0.3763***	0.3226***
	(5.59)	(-0.63)	(3.44)	(4.61)
Turnover	-0.0634***	0.0776	-0.0147***	-0.0022
	(-9.60)	(1.46)	(-2.60)	(-1.47)
Adj-R^2	8.67%	17.88%	7.15%	6.82%
N(Observations)	703,551	77,326	424,338	1,004,317

Panel B. Holding

Dep: IO(m)	1 QFII	2 RQFII	3 HKC	4 Local INST
Ret(m-3,m-1)	0.0073***	0.0004	0.0046	0.0475**
	(2.66)	(1.48)	(1.28)	(2.25)
Ret(m-12,m-4)	0.0054***	0.0005***	0.0041**	0.0215***
	(4.18)	(3.11)	(2.05)	(4.60)
Lnsize	0.0019***	0.0004***	0.0039***	0.0156***
	(4.93)	(11.13)	(8.52)	(6.97)
EP	-0.0582***	-0.0073***	-0.1009***	0.2387**
	(-6.03)	(-3.62)	(-4.41)	(2.23)
Turnover	-0.0040***	-0.0005***	-0.0021	-0.0363***
	(-5.79)	(-5.34)	(-1.58)	(-6.46)
LnAge	0.0007***	0.0002***	0.0009*	-0.0077***
	(4.09)	(10.90)	(1.68)	(-3.63)
LnPrice	0.0056***	0.0007***	0.0065***	0.0589***
	(30.48)	(23.21)	(11.11)	(28.75)
Dividend	0.1091***	0.0114**	0.1095***	-0.5687***
	(5.79)	(2.34)	(3.88)	(-7.89)
ROE	0.0145***	0.0009***	0.0229***	0.0929***
	(4.00)	(3.21)	(5.10)	(4.36)
Volatility	-0.0108***	-0.0008***	-0.0265***	-0.0574***
	(-2.77)	(-2.77)	(-4.45)	(-4.30)
Leverage	-0.0042***	-0.0003***	-0.0157***	0.0437***
	(-5.67)	(-5.61)	(-23.75)	(8.17)
Adj-R^2	20.73%	8.89%	16.41%	22.75%
N(observations)	31,866	31,866	18,843	31,866

Table 4 Stock return prediction of foreign investors and local institutions

This table presents estimation results on whether foreign investors and local institutions can predict the cross-sectional stock returns across both short-term and long-term horizons. Our sample period is from January 1, 2016, to June 30, 2019. We estimate daily Fama-MacBeth (1973) regressions. Panel A presents results on the next day's return prediction, as in equation (3). Panel B presents the coefficients on the order imbalance measure in the *w* week's cumulative return prediction. The key independent variable is the order imbalance measure on the previous day (*Oib(d-1)*). *Ret(d-1)* is the previous day's stock return. *Ret(d-6, d-2)* is the cumulative daily return over the [-6, -2] window. *Ret(d-27, d-7)* is the cumulative daily return over the [-27, -7] window. We include control variables: the log of market capitalization *(Lnsize)*, earnings-to-price ratio *(EP),* and monthly turnover *(Turnover)*, all measured at the end of the previous month. *Adj-R^2* is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. *Interquartile* is the time-series average of the cross-sectional interquartile range of the order imbalance variable. *Interquartile Return* represents the magnitude of investors' return predictability, defined as *Interquartile* multiplied by the estimated coefficient on the order imbalance. We adjust standard errors using Newey-West (1987) with five lags. For long-term return prediction, the lag number is two times the cumulative return days. We report *t*-statistics in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. One-day return prediction

Dep: Ret(d)	1	2	3	4
	QFII	RQFII	HKC	Local INST
Oib(d-1)	0.0649***	0.0247***	0.0783***	0.1330***
	(17.03)	(3.09)	(10.15)	(18.32)
Ret(d-1)	0.7388	-0.3870	0.2152	2.2033***
	(1.51)	(-0.61)	(0.36)	(4.21)
Ret(d-6, d-2)	-0.8924***	-0.5660**	-0.7376***	-1.1077***
	(-4.52)	(-2.08)	(-3.19)	(-5.89)
Ret(d-27, d-7)	-0.2353***	0.0237	-0.2095**	-0.3077***
	(-2.74)	(0.17)	(-2.04)	(-4.67)
Lnsize	-0.0078	0.0034	0.0045	-0.0016
	(-0.78)	(0.32)	(0.44)	(-0.15)
EP	1.3757***	1.2805	1.5416***	1.4607***
	(2.82)	(1.59)	(2.75)	(3.10)
Turnover	-0.0521***	-0.1848***	-0.1121***	-0.0556***
	(-2.62)	(-3.50)	(-4.31)	(-3.21)
Adj-R^2	8.96%	14.75%	10.07%	8.83%
N(observations)	787,197	143,723	444,489	1,007,350
Interquartile	1.8295	1.2342	0.9666	0.7012
Interquartile Return	0.1188%***	0.0305%***	0.0757%***	0.0933%***
	QFII-Local	RQFII-Local	HKC-Local	
Interquartile Return Difference	0.0255%***	-0.0626%***	-0.0184%***	
	(3.29)	(-5.52)	(-2.64)	

Panel B. 12-week cumulative return prediction

Dep: Cumulative Ret(w)	1	2	3	4	5	6	7
Week number w	QFII		RQFII		HKC		Local INST
1	0.1123***		0.0686***		0.0985***		0.2717***
2	0.1289***		0.1102***		0.1184***		0.3631***
3	0.1524***		0.1380***		0.1271***		0.4159***
4	0.1688***		0.1494**		0.1338**		0.4588***
5	0.1779***		0.2089***		0.1348**		0.4822***
6	0.1834***		0.2065**		0.1594**		0.5250***
7	0.2068***		0.2157**		0.1858**		0.5669***
8	0.2172***		0.2434**		0.1874**		0.6038***
9	0.2119***		0.2356*		0.1598		0.6010***
10	0.2284***		0.2665*		0.1701		0.6242***
11	0.2387***		0.3205**		0.1725		0.6375***
12	0.2507***		0.3240**		0.1677		0.6510***
Interquartile Cumulative Return	QFII	QFII-Local	RQFII	RQFII-Local	HKC	HKC-Local	Local INST
1	0.2054%***	0.0149%	0.0847%***	-0.1060%***	0.0952%***	-0.0946%***	0.1905%***
2	0.2358%***	-0.0188%	0.1361%***	-0.1191%**	0.1144%***	-0.1436%***	0.2546%***
3	0.2789%***	-0.0128%	0.1704%**	-0.1221%*	0.1228%***	-0.1725%***	0.2916%***
4	0.3088%***	-0.0129%	0.1844%***	-0.1381%	0.1293%**	-0.1917%***	0.3217%***
5	0.3255%***	-0.0127%	0.2578%**	-0.0815%	0.1303%**	-0.2091%***	0.3381%***
6	0.3356%***	-0.0325%	0.2549%**	-0.1146%	0.1541%**	-0.2141%***	0.3681%***
7	0.3784%***	-0.0191%	0.2662%**	-0.1331%	0.1796%**	-0.2185%***	0.3975%***
8	0.3973%***	-0.0261%	0.3004%**	-0.1243%	0.1811%**	-0.2431%***	0.4234%***
9	0.3877%***	-0.0337%	0.2908%*	-0.1325%	0.1544%	-0.2701%***	0.4214%***
10	0.4178%***	-0.0199%	0.3289%*	-0.1102%	0.1644%	-0.2734%**	0.4377%***
11	0.4367%***	-0.0103%	0.3956%**	-0.0527%	0.1667%	-0.2797%**	0.4470%***
12	0.4586%***	0.0021%	0.3999%**	-0.0576%	0.1621%	-0.2941%**	0.4565%***

Table 5 The Diversification and Liquidity Hypotheses

This table examines alternative hypotheses related to foreign investors' return predictive power. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. To test the diversification hypothesis, we compute the return correlations between stock i and the S&P 500 index using a rolling window of the previous 36 months with at least 24 non-missing observations. We define a dummy variable *HighDiv*, which is set to 1 if the correlation for stock i in month m is below the cross-sectional median, and 0 otherwise. We interact the order flow with the dummy variable in the previous month and estimate daily Fama-MacBeth regressions as in equation (4). Panel A presents the results. To examine the liquidity hypothesis, we rely on equation (2) and follow Boehmer, Jones, Zhang, and Zhang (2021), and decompose the foreign order flows into multiple components related to contrarian, persistence, and others. The contrarian component is calculated as the estimated coefficient $\widehat{a1}(d,G)$ times *Ret(i,d-1)*, the persistence component is calculated as the estimated coefficient $\widehat{a4}(d,G)$ times *Oib(i,d-1,G)* and the residual component is the intercept plus the regression residual $\hat{\epsilon}(i,d,G)$. Then we re-estimate equation (3) to assess the return predictive power of each of the above components. Panel B presents the results and related interquartile daily returns. *N(observations)* is the number of observations in the regressions. *Adj-R^2* is the time-series average of adjusted R-squared in the cross-sectional regression. To save space, we omit the coefficients on control variables. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. We report *t*-statistics in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. The diversification hypothesis

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1)	0.0614***	0.0299***	0.0707***	0.1284***
	(12.61)	(2.92)	(7.73)	(14.10)
Oib(d-1)× $HighDiv$(m-1)	0.0065	-0.0120	0.0182	0.0046
	(1.22)	(-0.92)	(1.56)	(0.46)
Adj-R^2	8.91%	15.13%	10.60%	8.27%
N(observations)	656,459	135,199	400,265	819,440

Panel B. The liquidity hypothesis

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib related to the contrarian trading	0.3367***	-1.3242	-0.9796	0.0184
	(3.50)	(-0.98)	(-1.20)	(0.02)
Oib related to the order flow persistence	0.4718***	0.2676	-0.1048	0.5854***
	(3.36)	(1.42)	(-0.71)	(13.67)
Oib residual	0.0678***	0.0296**	0.0813***	0.1177***
	(18.16)	(2.41)	(10.12)	(17.71)
Adj-R^2	9.92%	19.72%	11.02%	9.45%
N(observations)	701,132	77,137	423,688	1,001,039
Oib related to the past stock returns	0.0475%	-0.1519%	-0.0491%	0.0007%
Oib related to the previous day's order flow	0.1286%	0.0829%	-0.0146%	0.0861%
Oib related to the residual component	0.1042%	0.0271%	0.0726%	0.0780%

Table 6 Stock return predictive power: Foreign vs. Local

This table compares foreign investors' return predictive power to that of local investors. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month. In Panel A, we estimate Fama-MacBeth regressions as in equation (3) but replace foreign investors' order imbalance measure by *Oib(overlap with local)* and *Oib(foreign specific)*. In Panel B, we include both foreign capital flow and local foreign capital flow together and re-estimate equation (3). *Interquartile* is the time-series average of the cross-sectional interquartile ranges of investors' order flows. *Interquartile return* is defined as *Interquartile* multiplied by the estimated coefficient on the related order imbalance measure. *Adj-*R^2 is the time-series average of adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. Control variables are the same as those in equation (3). To save space, we omit the coefficients on control variables. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. We report *t*-statistics in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. foreign vs. local order flows: orthogonalization

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1, overlap with local)	0.3553	4.0874	1.9399	
	(0.18)	(1.14)	(0.84)	
Oib(d-1, foreign specific)	0.0593***	0.0197**	0.0700***	
	(15.67)	(2.45)	(10.02)	
Oib(d-1, overlap with foreign)				0.7173***
				(4.50)
Oib(d-1, local specific)				0.2355***
				(11.03)
Adj-R^2	9.18%	15.07%	10.32%	16.39%
N(observations)	780,128	143,670	444,414	104,111
Oib(d-1, overlap with local)	0.0399%	0.4916%	0.1330%	
Oib(d-1, foreign specific)	0.1034%	0.0240%	0.0670%	
Oib(d-1, overlap with foreign)				0.0769%
Oib(d-1, local specific)				0.1205%

Panel B. foreign vs. local order flows: incremental value

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC
Foreign Oib(d-1)	0.0593***	0.0197**	0.0700***
	(15.67)	(2.45)	(10.02)
Local Oib (d-1)	0.1465***	0.2285***	0.1699***
	(17.63)	(11.79)	(15.53)
Adj-R^2	9.18%	15.07%	10.32%
N(observations)	780,128	143,670	444,414
Interquartile Return			
Foreign Oib	0.1086%	0.0243%	0.0676%
Local Oib	0.1027%	0.1602%	0.1191%

Table 7 Stock return predictive power and firm-level information

This table presents stock return prediction results related to firm-level information. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month. Our sample covers 15,477 earnings announcements, 41,722 analyst-related events, and 353,551 financial media news days, wich account for 1.52%, 4.09% and 34.69% of all stock-day observations, respectively. We estimate equation (7) and present results in Panel A, B and C for earnings announcements, analyst-related events and financial media news, separately. The dependent variable *CAR* (*AR*) is the cumulative stock return minus the cumulative market return over the event period *[d, d+k]* (on day d). All dependent variables are expressed as percentages. *N(observations)* is the number of observations in the regressions. Control variables are the same as those in equation (3). The standard errors are adjusted using Newey-West (1987) following Table 4. To save space, we omit coefficients on control variables and *t*-statistics. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Earnings announcements

	1	2	3	4
	QFII	RQFII	HKC	Local INST
Coefficients on Oib(-1)				
AR[0]	0.0947***	0.0816	0.1517***	0.2678***
CAR[0,1]	0.1276***	0.0954	0.2478***	0.4210***
CAR[0,61]	0.2526**	0.2509***	0.1758***	1.2494***
CAR[0, 251]	0.2752	0.6640	-0.0270	1.9078***
Interquartile return				
AR[0]	0.1868%	0.1440%	0.1377%	0.1897%
CAR[0,1]	0.2518%	0.1684%	0.2249%	0.2981%
CAR[0,61]	0.4984%	0.4426%	0.1596%	0.8848%
CAR[0, 251]	0.5430%	1.1715%	-0.0245%	1.3510%

Panel B. Analyst-related events

	1	2	3	4
	QFII	RQFII	HKC	Local INST
Coefficients on Oib(-1)				
AR[0]	0.0746***	0.0622*	0.0884*	0.3853***
CAR[0,1]	0.1199***	0.1001**	0.1900**	0.5850***
CAR[0,61]	0.1819	0.3084	0.4023***	2.1092***
CAR[0, 251]	0.5705***	0.6992***	1.7120**	4.1002***
Interquartile return				
AR[0]	0.1441%	0.1245%	0.0764%	0.2321%
CAR[0,1]	0.2315%	0.2002%	0.1642%	0.3525%
CAR[0,61]	0.3512%	0.6168%	0.3476%	1.2707%
CAR[0, 251]	1.1014%	1.3984%	1.4794%	2.4701%

Panel C. Financial media news

	1 QFII	2 RQFII	3 HKC	4 Local INST
Coefficients on Oib(-1)				
AR[0]	0.0798***	0.0140**	0.0775***	0.1839***
CAR[0,1]	0.1300***	0.0390**	0.1307***	0.3061***
CAR[0,61]	0.3653***	0.2363**	0.2746***	1.1970***
CAR[0, 251]	0.5475***	0.6655***	0.9926*	1.9756***
Interquartile return				
AR[0]	0.1570%	0.0279%	0.0732%	0.1239%
CAR[0,1]	0.2559%	0.0779%	0.1235%	0.2063%
CAR[0,61]	0.7189%	0.4716%	0.2593%	0.8069%
CAR[0, 251]	1.0774%	1.3281%	0.9374%	1.3317%

Table 8 Stock return predictive power and information environment

This table presents estimation results on firms' information environment. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. In Panel A, B and C, we analyze the relation between foreign investors and firms with overseas business, analyst coverage, the top shareholder stock ownership, respectively. *Overseas* is the absolute value of the ratio of abroad revenue to total revenue in the half-year financial statement report. *Coverage* is the logarithm of the number of analyst plus one. *TopHolding* is defined as the top shareholder's holding shares divided by the total outstanding. In each Panel, we present results from two regressions. First, we investigate the relation between foreign holding and information environment by monthly Fama-MacBeth regressions similar to equation (2). The dependent variable *IO(i,m)* is the investors' holding shares divided by total outstanding floating shares for stock *i* in month *m*. The key independent is our metric in the previous month. Control variables are the previous three-month gross return *Ret(i,m-3,m-1)*, the nine-month gross return preceding the month *m-3*, *Ret(i,m-12,m-4)*, firm size, stock turnover ratio, and earnings-to-price ratio. Second, we investigate foreign investors' return predictive power by regressions similar to equation (4), where we replace *HighDiv* with our metric. All dependent variables are expressed as percentages. To save space, we omit coefficients on control variables. The standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. $Adj\text{-}R^2$ is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions.***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Overseas business

	1 QFII	2 RQFII	3 HKC	4 Local INST
1.Foreign holding				
$Overseas(m-1)$	0.0015***	-0.0005***	0.0007	0.0107**
	(2.99)	(-3.69)	(0.50)	(2.32)
Adj-R^2	12.51%	6.37%	8.52%	10.68%
N(Observations)	31,866	31,866	18,843	31,866
2.Return prediction				
Oib(d-1)	0.0625***	0.0216**	0.0747***	0.1293***
	(15.94)	(2.45)	(9.33)	(17.40)
Oib(d-1)× $Overseas(\mathrm{d}-1)$	0.0448**	0.0261	0.0690**	0.0568*
	(2.50)	(0.51)	(2.06)	(1.91)
Adj-R^2	8.97%	14.98%	10.05%	8.83%
N(Observations)	786,395	143,632	444,003	1,006,394

Panel B. Analyst coverage

	1	2	3	4
	QFII	RQFII	HKC	Local INST
1.Foreign holding				
$Coverage(m-1)$	0.0051***	0.0004***	0.0036***	0.0501***
	(19.15)	(4.43)	(5.53)	(43.33)
Adj-R^2	16.82%	6.84%	9.46%	18.22%
N(observations)	23,924	23,924	15,951	23,924
2.Return prediction				
Oib(d-1)	0.0645***	0.0131	0.0674***	0.1375***
	(16.83)	(0.87)	(8.56)	(18.03)
Oib(d-1)× $Coverage(d-1)$	0.0025	0.0091	0.0273***	0.0212***
	(0.84)	(0.85)	(5.00)	(3.47)
Adj-R^2	8.99%	15.03%	10.09%	8.87%
N(observations)	787,197	143,723	444,489	1,007,350

Panel C. Top shareholder

	1	2	3	4
	QFII	RQFII	HKC	Local INST
1.Foreign holding				
$TopHolding(m-1)$	-0.0087***	-0.0005*	-0.0090***	-0.14015***
	(-4.69)	(-1.77)	(-9.30)	(-13.04)
Adj-R^2	14.74%	6.47%	11.26%	14.37%
N(Observations)	28,966	28,966	16,801	28,966
2.Return prediction				
Oib(d-1)	0.0799***	0.0260	0.0784***	0.1295***
	(9.81)	(1.24)	(5.51)	(9.42)
Oib(d-1)× $TopHolding(d-1)$	-0.0422**	0.0039	-0.0043	0.0093
	(-2.31)	(0.08)	(-0.15)	(0.32)
Adj-R^2	8.44%	13.56%	9.51%	8.16%
N(Observations)	700,356	117,340	394,412	892,461

Table 9 Trend test, regulations, counterparties and account performance

This table presents results about trend tests on market information environment indicators, regulations on stock market liberalization, counterparties and foreign investors' account performance. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. Panel A examines the trend of different information environment indicators. We regress the time-series scores of market-level indicators on a *Trend* variable, which is equal to the year number. In Panel B, we regress the time series of the estimated coefficient $\widehat{c1}$ from equation (3) on regulation dummies as in equation (8). *Quota2016, Quota2017, Quota2018, Quota2019* refer to the extension of investment quotas for foreign investors; *Access2016* signifies the removal of equity investment; and *Lockup2018* denotes the abolition of capital lock-up periods. Each dummy variable is equal to zero before the related event occurs and one afterward, as explained in the Internet Appendix IA.III. In Panel C, we separate counterparties into three groups: foreign investors, local institutions, and retail investors (RT). According to the sign of order imbalances, we separate investors' daily trade directions into buy (B) and sell (S). With the three groups of investors and two sides of the trade, all observations are divided into six bins: BBS, SSB, BSS, SBB, BSB, and SBS. The first letter indicates the trade direction of foreign investors, the second indicates the trade direction of local institutions, and the third for retail investors. Then we examine whether foreign investors' return predictive pattern changes with different counterparties with Fama-MacBeth regressions as in equation (9). The indicator variable *I(k,d,G)* is equal to one if trades from foreign investor group *G* for stock *i* on day *d-1* fall in the *k*-th counterparty bin, otherwise, it is zero. In Panel D, we compute the total gain net of risk-free profits for each investor group. The total account performance equals the capital gain from holdings plus trading proceeds minus transaction costs. Transaction costs include commission cost (0.05%) imposed on both the buy and sell side (with a minimum of 5 CNY for each trade), the stamp tax (0.10% of the sales amount), and the transfer fee (0.002% imposed on both sides). We add up all the daily gains from the entire sample and divide the total number by 3.5 to get the annual performance. We further decompose the performance into stock selection, market timing, and transaction costs. Intuitively, the stock selection component captures whether investors can achieve better performance by actively selecting stocks that outperform the stock market. The market timing component captures whether the investors can strategically make investment decisions based on the relative performance between the stock market portfolio and the risk-free asset, and thus, time the market. To have a sense of the return percentage of investment, we divide the account gains by the aggregate holding value in the previous day, and cumulate the daily return to obtain the annual performance. The dependent variables are expressed in percentages. All control variables are the same as those in equation (3). To account for serial correlation in the coefficients, the standard errors of the time series are adjusted using Newey-West (1987) with 5 lags. We report *t*-statistics in parentheses. *Adj-R^2* is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Trend test

	1 The prevalence of foreign ownership	2 The extent of shareholder rights	3 The strength of auditing and reporting standards
Trend	0.0259***	0.3928***	0.0207*
	(2.72)	(3.59)	(1.78)
Intercept	-47.8426**	-788***	-37.2543
	(-2.49)	(-3.57)	(-1.59)
Adj-R^2	47.85%	66.43%	26.55%
N(observations)	8	7	7

Panel B. Regulations

Dep: $\widehat{c1}(d)$	1 QFII	2 RQFII	3 HKC
Intercept	0.0095	0.0233	0.0289***
	(0.61)	(1.09)	(3.43)
Quota2016(d-1)	0.0615***	0.0064	0.0234**
	(3.53)	(0.23)	(2.05)
Access2016(d-1)	-0.0042	-0.0085	
	(-0.44)	(-0.33)	
Quota2017(d-1)		-0.0063	
		(-0.26)	
Quota2018(d-1)		-0.0265	0.0913***
		(-0.83)	(5.25)
Lockup2018(d-1)	0.0040	0.0484	
	(0.37)	(1.49)	
Quota2019(d-1)	-0.0187	0.0127	
	(-1.18)	(0.29)	
Adj-R^2	0.49%	-0.51%	6.58%
N(observations)	849	847	809

Panel C. Predictive patterns with different counterparties

Dep: Ret(d)	1	2	3
	QFII	RQFII	HKC
Oib(d-1)*BBS	0.0500***	0.0694	0.1890***
	(4.06)	(1.32)	(9.92)
Oib(d-1)*SSB	0.2009***	0.1194**	0.1188***
	(15.63)	(2.34)	(6.80)
Oib(d-1)*BSS	-0.0097	-0.0558	0.0808***
	(-0.56)	(-0.84)	(3.44)
Oib(d-1)*SBB	0.1388***	0.1139*	0.0612**
	(7.72)	(1.84)	(2.23)
Oib(d-1)*BSB	-0.0749***	-0.0412	0.0009
	(-5.78)	(-0.78)	(0.04)
Oib(d-1)*SBS	0.0432***	-0.0744	-0.0729***
	(3.27)	(-1.44)	(-3.91)
N(observations)	755,991	133,172	430,067
Interquartile return			
BBS	0.0101%***	0.0049%	0.0940%***
SSB	0.0333%***	0.0075%**	0.0633%***
BSS	-0.0017%	-0.0049%	0.0342%***
SBB	0.0226%***	0.0089%*	0.0275%**
BSB	-0.0185%***	-0.0033%	0.0004%
SBS	0.0108%***	-0.0059%	-0.0379%***

Panel D. Account performance

Investor	Total (billion CNY)	Cost (billion CNY)	Stock selection (billion CNY)	Market timing (billion CNY)	Total (%)	Cost (%)	Stock selection (%)	Market timing (%)
QFII	40.48	-0.74	49.88	-8.66	17.79%	-0.31%	22.35%	-3.85%
RQFII	11.97	-0.08	13.57	-1.52	20.81%	-0.14%	25.47%	-4.01%
HKC	60.62	-2.08	64.85	-2.16	17.73%	-0.61%	22.35%	-3.67%
Local INST	376.58	-13.93	504.01	-113.50	10.22%	-0.40%	15.03%	-3.91%

Table 10 Robustness checks

This table presents results for several robustness checks. The sample period is from January 2016 to June 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. In Panels A and B, we require non-missing order flows from both foreign and local investors at stock-day level, then we estimate one-day and long-term return prediction regressions, separately. In Panel C, we replace missing order flow variables with zeros and estimate one-day return prediction regressions. In Panel D, we remove observations (representing 1.71% of the total sample) where stocks hit the daily price limits and re-estimate the daily return predictive regression. In Panel E, we skip day *d* and examine the order flows' predictive power for stock returns on day *d+1*. In Panel F, we also include order imbalances from all four investor groups together in one regression to predict the next day's return. *Interquartile Return* represents the magnitude of investors' return predictability, defined as *Interquartile* multiplied by the estimated coefficient on the order imbalance. All dependent variables are in percentages. To spare space, we generally omit coefficients on control variables and *t*-statistics and report the number of observations. The standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. The lag number for long-term return prediction in Panel B is two times the cumulative return days. *Adj-R^2* is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. One-day return prediction with non-missing observations in all investor groups

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1)	0.0726***	0.0357***	0.1022***	0.2490***
	(7.48)	(4.04)	(5.30)	(11.59)
Adj-R^2	8.05%	13.61%	12.11%	13.70%
N(observations)	104,111	104,111	104,111	104,111
Interquartile	1.5551	1.1724	0.7888	0.5283
Interquartile Return	0.1129%***	0.0419%***	0.0806%***	0.1316%***

Panel B. 12-week cumulative return prediction with non-missing observations in investor groups

Interquartile Cumulative Return Week number *w*	1 QFII	2 RQFII	3 HKC	4 Local INST
1	0.1307%***	0.0974%***	0.0497%	0.1849%***
2	0.1300%***	0.1399%***	0.0926%	0.2912%***
3	0.1602%***	0.1615%***	0.0856%	0.3303%***
4	0.1944%**	0.1745%**	0.1049%	0.3888%***
5	0.1744%*	0.1986%**	0.1219%	0.4446%***
6	0.2190%**	0.1722%*	0.1280%	0.4780%***
7	0.2426%**	0.1964%	0.1449%	0.5383%***
8	0.2839%**	0.2147%	0.1950%	0.5501%***
9	0.2783%***	0.2019%	0.1558%	0.5289%***
10	0.3819%***	0.2338%	0.1673%	0.6369%***
11	0.4053%***	0.3366%*	0.1935%	0.6105%***
12	0.4777%***	0.3784%*	0.2054%	0.6109%***

Panel C. Replace the missing value of order flows with zero in the one-day return prediction.

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1)	0.0615***	0.0174**	0.0751***	0.1284***
	(15.49)	(2.16)	(9.95)	(17.89)
Adj-R^2	8.75%	8.65%	8.70%	8.78%
N(observations)	1,019,052	1,019,052	1,019,052	1,019,052
Interquartile	1.4957	0.0437	0.1078	0.6928
Interquartile Return	0.0919%***	0.0008%**	0.0081%	0.0890%***

Panel D. Return prediction when no price limits happen on day d-1

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1)	0.0707***	0.0261***	0.0941***	0.1725***
	(18.88)	(3.26)	(11.15)	(22.14)
Adj-R^2	9.2%	14.5%	10.2%	9.1%
N(observations)	775,565	142,618	439,980	991,189
Interquartile	1.8259	1.2347	0.9651	0.6988
Interquartile Return	0.1292%	0.0323%	0.0908%	0.1205%
	QFII-Local	RQFII-Local	HKC-Local	
Interquartile Return Difference	0.0087%	-0.0882%***	-0.0301%***	

Panel E. Predict stock returns on day d+1

Dep: Ret(d+1)	1 QFII	2 RQFII	3 HKC	4 Local INST
Oib(d-1)	0.0399***	0.0181**	0.0414***	0.1043***
	(11.25)	(2.14)	(5.74)	(16.02)
Adj-R^2	8.3%	14.1%	9.4%	8.1%
N(observations)	784,516	143,332	443,179	1,004,041
Interquartile	1.8295	1.2342	0.9666	0.7012
Interquartile Return	0.0730%	0.0224%	0.0400%	0.0731%
	QFII-Local	RQFII-Local	HKC-Local	
Interquartile Return Difference	-0.0001%	-0.0504%***	-0.0343%***	

Panel F. Horse race test

Dep: Ret(d)	1
QFII(d-1)	0.0600***
RQFII(d-1)	0.0248***
HKC(d-1)	0.0842***
Local INST(d-1)	0.2410***
Adj-R^2	17.13%
N(observations)	10,411
Interquartile Return	
QFII	0.0933%
RQFII	0.0291%
HKC	0.0664%
Local INST	0.1273%

Figure 1 The timeline of QFII, RQFII, and HKC in China

This figure presents the key events during the development of QFII, RQFII, and HKC in the Chinese stock market. The first layer about investment quota is in black font, the second layer about capital control and local-up period is in green font, and the third layer about investment accessibility is in blue.

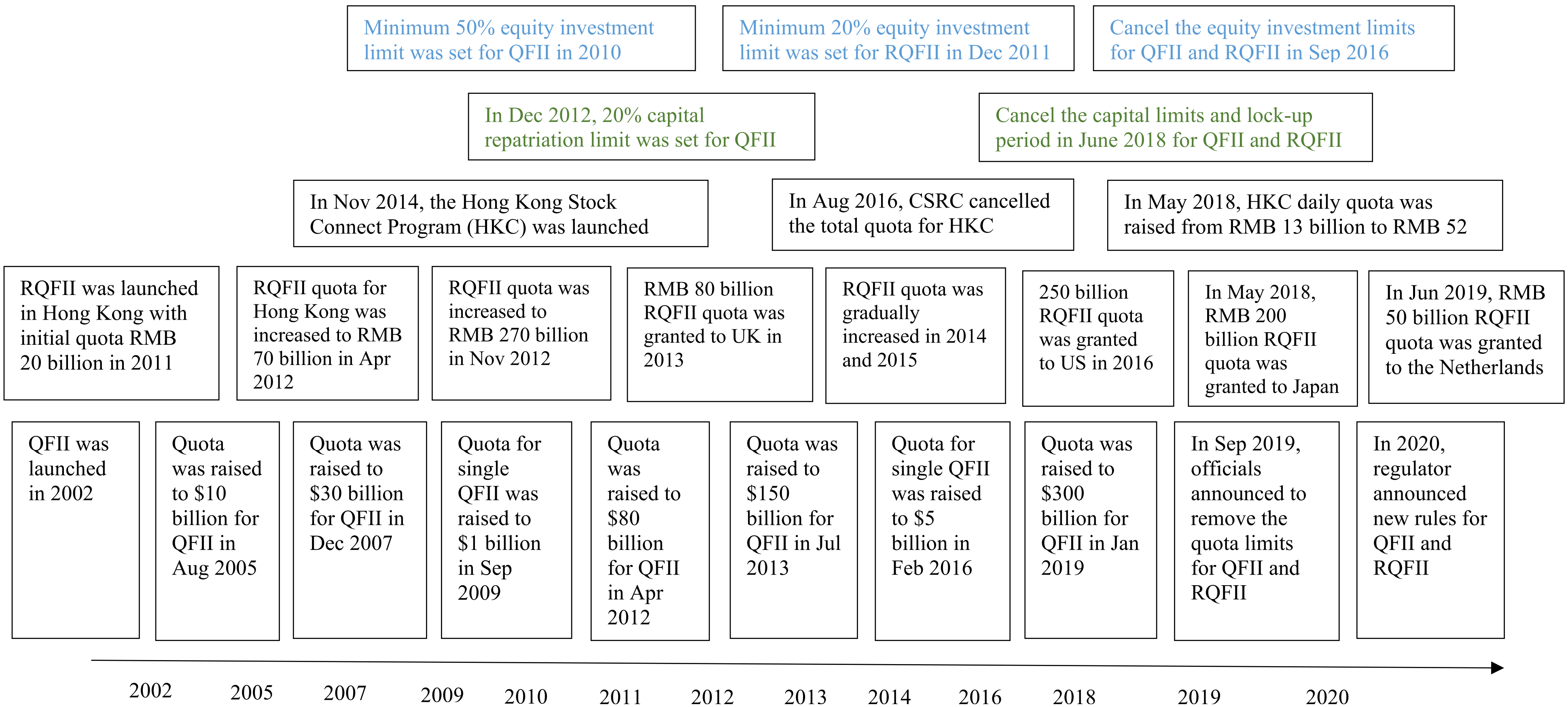
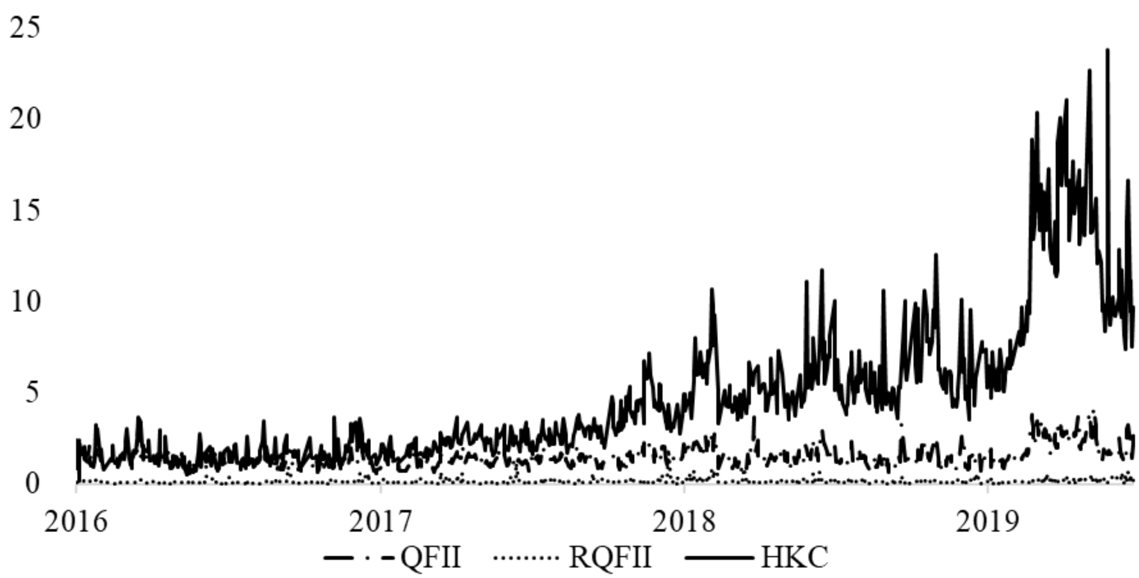


Figure 2 Aggregate trading and holding for QFII, RQFII, and HKC

The figure shows the time-series aggregate trading volume and holdings by QFII, RQFII, and HKC from January 1, 2016, to June 30, 2019. Panel A shows the time-series aggregate trading volume in billion RMB. Panel B shows the time-series aggregate holdings in billion RMB

Panel A. Aggregate trading volume in billion RMB



Panel B. Aggregate holding in billion RMB

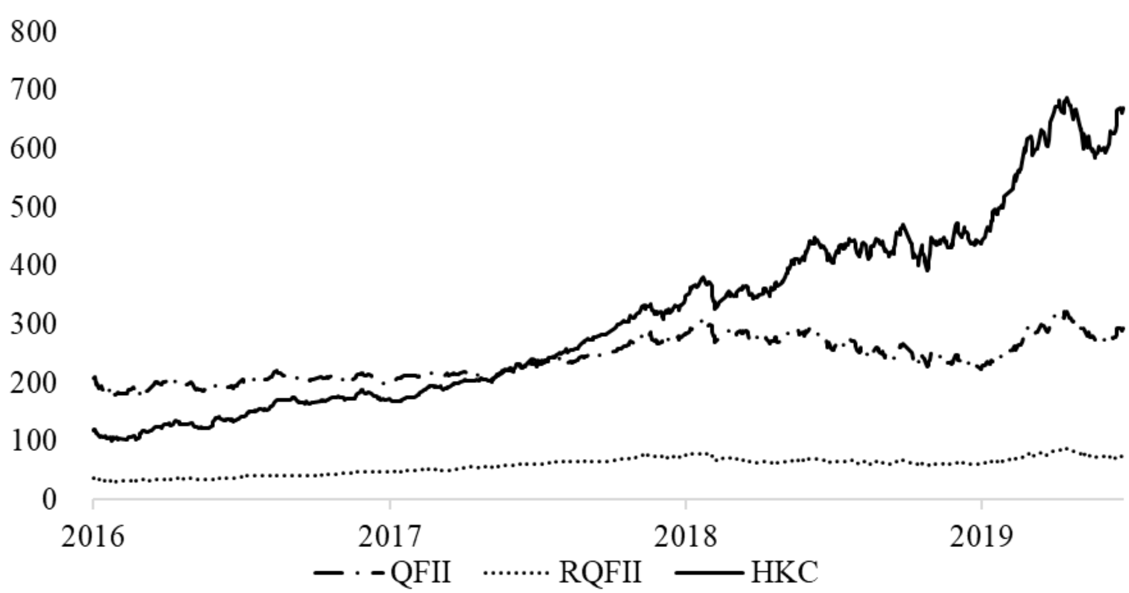


Figure 3 Investors' return predictive power over longer horizons

In this figure, we present the cumulative interquartile returns and the two standard deviation bands for foreign investors and local institutions over the subsequent 12 weeks. The cumulative interquartile returns are calculated as the interquartile of order imbalance multiplied by the coefficients of order imbalance in Table 4 Panel B. The standard errors are calculated following Newey and West (1987) with lag numbers of two times the cumulative return days.

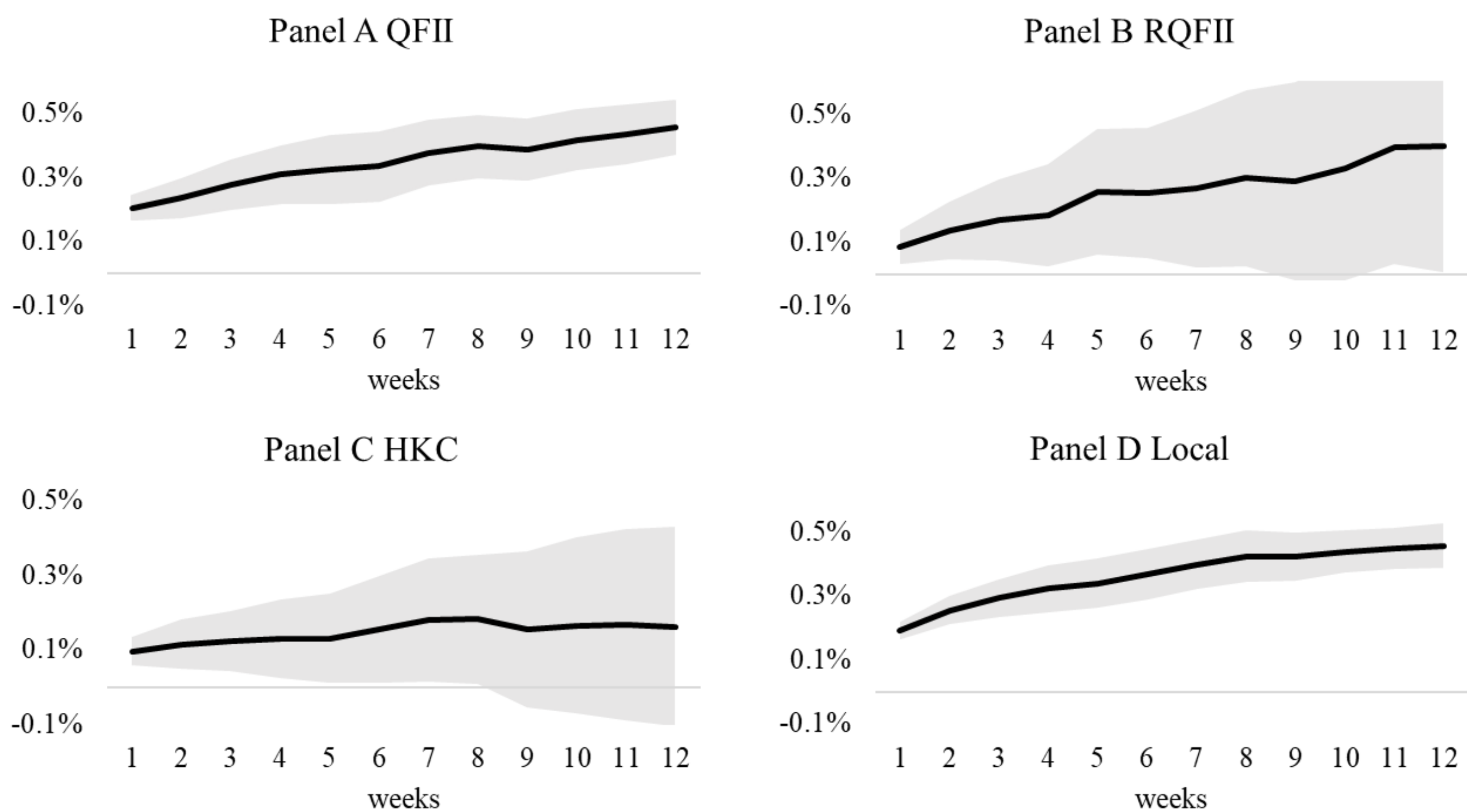
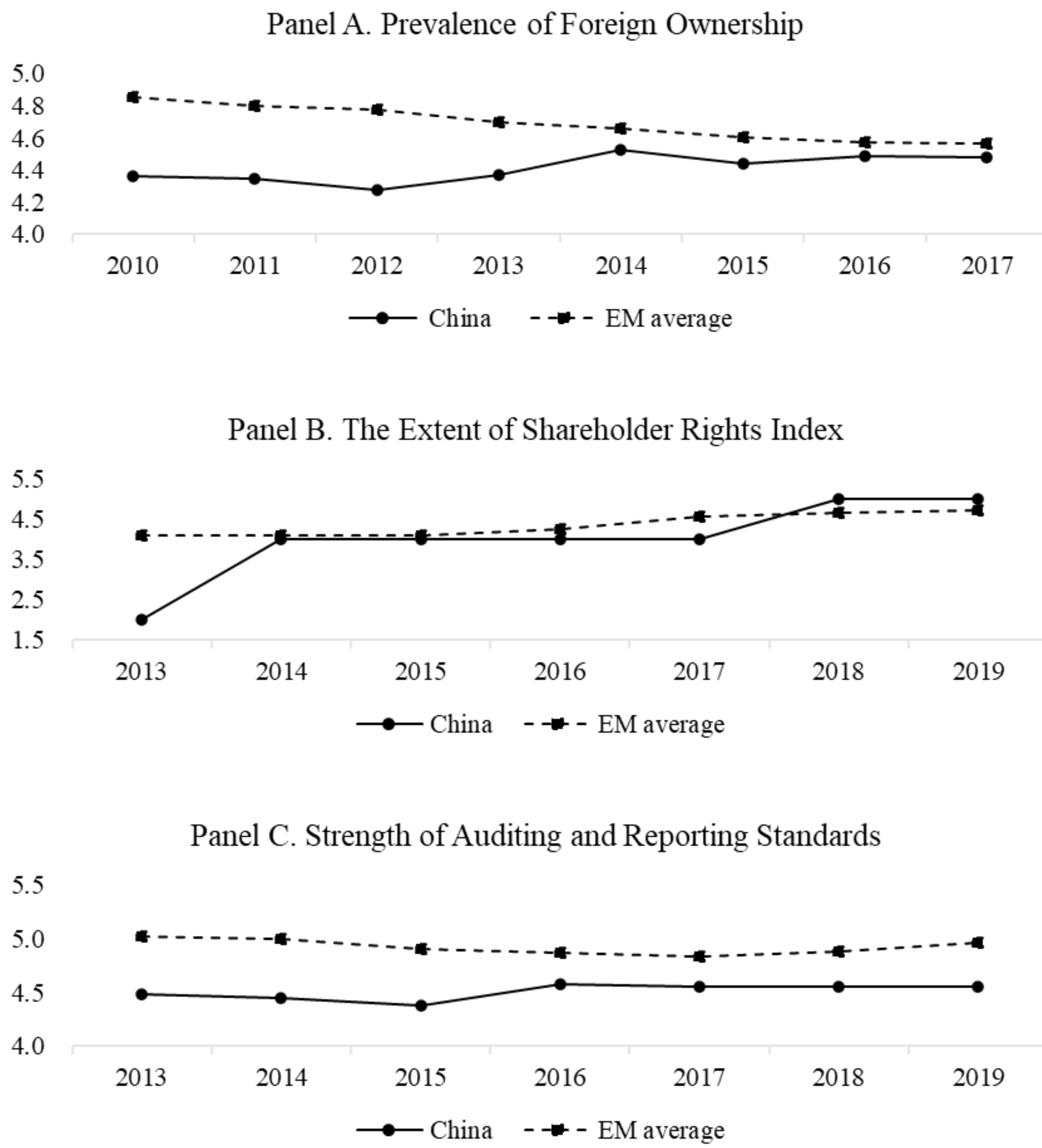


Figure 4 Market-level information environment indicators

This figure shows a time series of market-level indicators for China and developing markets. Panel A plots the World Economic Forum's prevalence of foreign ownership index, with one representing highly rare foreign ownership in local firms and 7 indicating extremely prevalent foreign ownership. Panel B plots the extent of shareholder rights index from the World Bank, which evaluates shareholders' roles in critical corporate decisions (0=less rights, 6=more rights). Panel C shows the World Economic Forum's auditing and accounting standards index, with 1 representing extremely weak financial auditing and reporting standards and 7 indicating exceptionally good standards.



Internet Appendix to

"Foreign Capital in the Chinese Stock Market: A Firm Level Study"

IA.I Analyst Dataset

To build a comprehensive analyst dataset, we obtain analyst forecasts and recommendations data from four leading data vendors in China: CSMAR, WIND, RESSET, and SUNTIME. Following Li, Wong, and Yu (2020), we start with the CSMAR analyst database and add new observations from the other three. To ensure accuracy, we require that the observation in the final dataset be recorded in at least two of the four databases with the same analyst forecast.

We only include firm-level annual EPS earnings forecasts made for the current fiscal year before the earnings announcements. The stocks' consensus forecast is the arithmetic average of all outstanding EPS forecasts made since the last earnings announcement date. We calculate the forecast revision as the current consensus forecast minus the previous consensus forecast. In terms of recommendations, these databases usually divide them into five categories: strong buy, buy, hold, sell, and strong sell. We keep the original rankings in the databases and assign numerical values of 2, 1, 0, -1, and -2 to strong buy, buy, hold, sell, and strong sell, respectively. The analyst's recommendation change is the current numeric recommendation minus the previous recommendation made by the same analyst within one year (Jia, Wang and Xiong, 2017). If no previous recommendation matches, the change is the difference between the current recommendation and zero. Finally, we compute the mean of analyst recommendation at the stock-day level.

IA.II Foreign Order Flows and Firm-Level Information

In this section, we apply a different methodology to investigate foreign investors' informativeness on earnings news. If investors can access or anticipate the information in earnings news, their order flows ahead of events should have greater predictive power on event days than on non-event days. Notice that some news is fully expected and hence leads to little or no reaction in realized returns, whereas other news items are unexpected and lead to large reactions in returns. Therefore, we further separate the event days into big-news days and no-big-news days. Following Jiang and Zhu (2017), we use large stock price jumps to identify significant information events. First, we compute the 5th and 95th percentiles of earnings announcement day return across all firms and all days in the previous quarter to separate the largest reactions of returns to the information, indicating that these events are most value-relevant. We define an indicator $Bignews(i, d)$, which is equal to 1 if stock i's return on earnings announcement day d in quarter q is outside of the 5th and 95th percentiles of earnings announcement day return in quarter $q - 1$, and is zero otherwise. Similarly, we define another indicator, $NBignews(i, d)$, which is equal to 1 if stock i's return on earnings announcement day d in quarter q is within the 5th and 95th percentiles of all earnings announcement day returns in quarter $q - 1$, and is zero otherwise. Empirically, we separately estimate the predictive power of order flows for future returns on the most and least value-relevant events in the following design for each quarter q:

$$
\begin{aligned}
\text{(IA1)} \qquad Ret(i, d) = {} & h0(q, G) \\
& + [h1(q, G) + h2(q, G)\, Bignews(i, d) \\
& + h3(q, G) NBignews(i, d)] \times Oib(i, d - 1, G) \\
& + h4(q, G)' Controls(i, d) + \epsilon(i, d, G).
\end{aligned}
$$

Here, we interact investors' order flows with the two indicators to allow the predictive power to differ on the most and least value-relevant earnings announcement events. If the next day is a non-event day, $h1(G)$ captures the predictive relation between order flows and future returns. If the next day is an earnings announcement day with large price movements, $h1(G) +$

$h2(G)$ captures the predictive relation between order flows and future returns. Similarly, if the next day is an earnings announcement day without large price movements, $h1(G) + h3(G)$ captures the predictive relation between order flows and future returns. Coefficient estimates, $h2(G)$ and $h3(G)$, tell whether investor group G has higher return predictive power on scheduled event days than non-event days. The differences in coefficients, $h2(G)$ and $h3(G)$, tell us whether the investors process information related to large price movements.

Table IA2 Panel A provides results for estimating the equation (IA1). For QFII, the $\widehat{h1}$, $\widehat{h2}$ and $\widehat{h3}$ coefficients are 0.0976, 0.8277, and -0.0159, respectively, all significant at the 95% confidence level. The interquartile return on non-event days is 0.0976*1.8295*0.01=0.1786%, the interquartile return on event days with large price changes is (0.0976+0.8277)*1.8295*0.01=1.6928%, and the interquartile return on event days with small price changes is (0.0976-0.0159) *1.8295*0.01=0.1496%. That is, the predictive power of QFII for future stock returns is quite similar for non-event days and event days with no large price changes, while for event days with large returns, their predictive power is almost six times higher. These results show that QFIIs anticipate firm information when the most value-relevant news becomes public the next day. Similar patterns are observed for order flows from RQFIIs, HKC, and local institutions. In terms of economic magnitude, computed using interquartile returns, QFII has the strongest return predictive power on the most value-relevant news days across the three foreign investor groups.

Following Boehmer et al. (2020), we gauge the importance of firm events to investors' overall performance using the fact that 0.14% of the sample are earnings announcements with large price changes, and 1.38% of the sample are events with small price changes. Take QFII as an example. The overall performance is the sum of interquartile returns on earnings announcement days multiplied by the percentage of event days in the total sample, 0.1786%*(1-1.52%)+1.6928%*0.14%+0.1496%*1.38%=0.1803%. Thus, event days with large price changes account for (1.6928%*0.14%)/0.1803%=1.31% of the overall performance, and other event days account for (0.1496%*1.38%)/0.1803%=1.14%. The results indicate that events with large price changes are important sources of investors' return predictive power. The contribution of the most valuable earnings announcement days for RQFII and HKC exhibits similar patterns.

We also execute similar exercise for analyst-related events and financial media news in Table IA2 Panel B and C, respectively. All patterns are similar. Overall, these results support H2, as we find that foreign investors are capable of processing local firm prescheduled information related to earnings announcements, especially regarding events leading to large price movements.

IA.III Regulations

China gradually relaxed the QFII, RQFII, and HKC regulations during our sample period to attract more foreign capital flows. These reforms facilitated the entrance of foreign investors to the Chinese market, which also allows us to examine how foreign investors' return predictive power evolves along with a greater degree of regulatory freedom. Our sample includes four major policy changes for the QFII program. First, on February 3, 2016, SAFE announced an increase in the maximum basic investment quota for a single QFII from $1 billion to $5 billion. Second, on September 30, 2016, CSRC announced the removal of a requirement for QFII, which required the equity investment portion of their portfolios to be above 50%. Third, on June 10, 2018, SAFE announced the removal of the 3-month lock-up period and the maximum 20% capital repatriation limitation for QFII. Finally, on January 14, 2019, SAFE announced an increase in QFII's total investment quota from $150 billion to $300 billion. There are six major policy changes for the RQFII program. First, regulators announced an RMB 250 billion quota to the US on June 7, 2016. Second, RQFIIs originally were not allowed to invest in stocks or stock investment funds at levels that exceeded 20% of their raised capital, and CSRC announced lifting that restriction at a press conference on September 30, 2016. Third, on July 4, 2017, authorities raised Hong Kong's investment quota to RMB 500 billion. Fourth, on May 9, 2018, officials declared an RMB 200 billion quota for Japan. Fifth, SAFE decided on June 11, 2018, that the three-month lock-up period for RQFII would no longer apply. Sixth, on June 5, 2019, authorities proclaimed an RMB 50 billion quota for the Netherlands. There are two regulatory changes for the HKC program. First, on August 16, 2016, the RMB 300 billion aggregated quota was removed. Second, on May 1, 2018, the daily quota increased from RMB 13 billion to RMB 52 billion. Based on these regulations, we define several regulation dummy variables. *Quota2016, Quota2017, Quota2018,* and *Quota2019* refer to the extension of investment quotas for foreign investors; *Access2016* signifies the removal of equity investment; and *Lockup2018* denotes the abolition of capital lock-up periods. Each dummy variable is equal to zero before the related event occurs and one afterward.

IA.IV Account Performance Decomposition

This section explains how we calculate the account performance in Section V.D. First, we design a methodology to obtain an estimate of the aggregate performance of foreign investors and local institutions as in equation (IA2),

$$\text{(IA2)} \quad Total(d,G) = \sum_{i=1}^{N} \Big[HoldShares(i,d,G) * \big(close(i,d) + dividend(i,d)\big) - HoldShares(i,d-1,G) * close(i,d-1) * (1 + rf(d)) \Big] +$$

$$\sum_{i=1}^{N}[SellShare(i,d,G) * SellPrice(i,d,G) - BuyShares(i,d,G) * BuyPrice(i,d,G)] * (1 + rf(d)) - \sum_{i=1}^{N} TrdCost(i,d,G).$$

$HoldShares(i,d,G)$ is the total shares held by investor group G for stock i on day d; $close(i,d)$ is the closing price; $dividend(i,d)$ captures any cash payout; $SellShares(i,d,G)$ ($BuyShares$) captures the shares sold (purchased) by investor group G; and $SellPrice(i,d,G)$ ($BuyPrice$) captures the average selling (purchasing) price. Then we break down an investor's account performance into stock selection, market timing, and transaction costs, as shown in (IA3):

(IA3) $$Total(d,G) = StkSelect(d,G) + MktTiming(d,G) - TrdCost(d,G).$$

The stock selection component is calculated as in equation (IA4),

(IA4) $$StkSelect(d,G) = \sum_{i=1}^{N} HoldShares(i,d-1,G) * close(i,d-1) * [Ret(i,d) - MktRet(d)] + \sum_{i=1}^{N} BuyShares(i,d,G) * BuyPrice(i,d,G) * [Ret(i,d) - MktRet(d)] - \sum_{i=1}^{N} SellShares(i,d,G) * SellPrice(i,d,G) * [Ret(i,d) - MktRet(d)].$$

$Ret(i,d)$ is the close price, $close(i,d)$, plus the cash dividend, $dividend(i,d)$, divided by the close price on day *d-1*. $MktRet(d)$ is the return on a value-weighted market portfolio, and $rf(d)$ is the risk-free rate. The first component is related to the capital gain. Here $HoldShares(i,d,G)$ is the total holding shares of investor group G for stock i on day d. As a result, the capital gain is equal to the holding values on day *d-1* times by the market-adjusted stock return on day d. The second and third components, which use a similar formula, capture the market-adjusted performance from investors' buy and sell. Here $SellShares(i,d,G)$ ($BuyShares$) is the shares of sell (buy) of investor group G for stock i on day d; $SellPrice(i,d,G)$ ($BuyPrice$) is the average sell (buy) price, calculated as the total value of sells (buys) of investor group G for stock *i* on day *d* divided by the shares. Overall, the stock selection captures whether investors have better performance by actively selecting stocks that outperform the stock market.

The market timing is calculated in equation (IA5),

(IA5) $$MktTiming(d,G) = \sum_i [HoldShares(i,d-1,G) * close(i,d-1) + BuyShares(i,d,G) * BuyPrice(i,d,G) - SellShares(i,d,G) * SellPrice(i,d,G)] * [MktRet(d) - rf(d)].$$

Therefore, the market timing component captures whether the investor can strategically make investment decisions based on the relative performance between the stock market portfolio and bonds (risk-free rate), and thus, time the market.

Because holding shares on day *d* generally equals holding shares on day *d-1* plus the net trading volumes (buy volumes – sell volumes) on day *d*, we can replace $HoldShares(i,d-1,G)$ in equation (IA4) and (IA5) by $HoldShares(i,d,G)$, $BuyShares(i,d,G)$ and $SellShares(i,d,G)$. Then, combining market timing, stock selection, and transaction costs will yield the total performance in equation (IA2).

Table IA1 Stocks characteristics, sectors and investors' trading and holding behaviors

This table presents summary statistics on stock characteristics and sectors conditional on investors' trading and holding behaviors from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month and we match these stocks with the investors' trading information. In Panel A, on each day, we sort stocks into two groups based on investors' daily holding shares in percentage of stocks' A-share outstanding. Then we calculate the time-series average of the cross-sectional mean of stocks' size (in billion RMB), earnings-to-price ratio and monthly turnover. We also present sectors classified by CSRC with the lowest and highest investors' holdings at the industry level. In Panel B, we sort stocks into two groups based on investors daily trading volumes in percentage of total volume and report similar statistics.

Panel A. Size, earnings-to-price ratio, turnover and sectors conditional on investors' holdings

	QFII		RQFII		HKC		Local INST	
	Low	High	Low	High	Low	High	Low	High
Size	10.36	37.19	11.91	35.65	8.27	39.28	19.27	28.29
EP	0.0036	0.0096	0.0045	0.0087	0.0035	0.0097	0.0045	0.0088
Turnover	61.94%	36.24%	67.93%	30.26%	68.99%	29.20%	60.68%	37.50%
Sector	Education	Manufacturing	Education	Manufacturing	Education	Manufacturing	Education	Finance

Panel B. Size, earnings-to-price ratio, turnover and sectors conditional on investors' trading

	QFII		RQFII		HKC		Local INST	
	Low	High	Low	High	Low	High	Low	High
Size	14.31	33.28	12.79	100.02	7.02	43.03	11.07	36.48
EP	0.0055	0.0077	0.0056	0.0133	0.0036	0.0101	0.0038	0.0094
Turnover	60.81%	37.37%	53.94%	22.87%	65.11%	31.10%	68.82%	29.37%
Sector	Education	Manufacturing	Education	Manufacturing	Education	Manufacturing	Education	Manufacturing

Table IA2 Foreign investors' stock return predictive power and firm-level news

This table presents results on investors' stock return predictive power around different types of firm-level news. The sample period is from January 2016 to June 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month, and we match these stocks with the investors' trading information. First, we estimate the quarterly Fama-MacBeth regressions as in equation (IA1) and present results in Panel A. In Panels B and C, we re-estimate the regressions in equation (IA1) but focus on analyst-related events and financial media news, respectively. All dependent variables are expressed in percentages. *N(observations)* is the number of observations in the regressions. Control variables are the same as those in equation (3). The standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. To save space, we omit coefficients on control variables and *t*-statistics in the table and report the number of observations. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Stock return prediction with earnings announcements

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
$\widehat{h1}$: Oib(d-1)	0.0976***	0.0497***	0.0993***	0.2198***
$\widehat{h2}$: Oib(d-1)×Bignews(d)	0.8277**	1.3634***	-0.2439	2.3619***
$\widehat{h3}$: Oib(d-1)×NBignews(d)	-0.0159	-0.0488	0.0887**	-0.1359**
N(observations)	787,197	143,723	444,489	1,007,350
Interquartile (Oib)× $\widehat{h1}$	0.1786%	0.0614%	0.0960%	0.1542%
Interquartile(Oib)× $(\widehat{h1}+\widehat{h2})$	1.6928%	1.7441%	-0.1398%	1.8103%
Interquartile(Oib× $(\widehat{h1}+\widehat{h3})$	0.1496%	0.0012%	0.1817%	0.0589%
Contribution of Bignews days (0.14%)	1.31%	3.88%	-0.20%	1.63%
Contribution of NBignews days (1.38%)	1.14%	0.03%	2.59%	0.52%

Panel B. Stock return prediction with analyst-related news

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
$\widehat{h1}$: Oib(d-1)	0.0970***	0.0423**	0.0938***	0.1781***
$\widehat{h2}$: Oib(d-1)×Bignews(d)	0.3884**	0.7231***	0.3056	2.9725***
$\widehat{h3}$: Oib(d-1)×NBignews(d)	-0.0388***	0.0284	0.1044*	0.0384*
N(observations)	744,205	131,276	415,655	951,793
Interquartile (Oib)× $\widehat{h1}$	0.1774%	0.0522%	0.0907%	0.1249%
Interquartile(Oib)× $(\widehat{h1}+\widehat{h2})$	0.8881%	0.9447%	0.3861%	2.2093%
Interquartile(Oib× $(\widehat{h1}+\widehat{h3})$	0.1065%	0.0873%	0.1917%	0.1518%
Contribution of Bignews days (0.44%)	2.20%	7.96%	1.96%	7.94%
Contribution of NBignews days (3.69%)	2.21%	6.68%	8.82%	4.96%

Panel C. Stock return prediction with media news

Dep: Ret(d)	1 QFII	2 RQFII	3 HKC	4 Local INST
$\widehat{h1}$: Oib(d-1)	0.0924***	0.0310*	0.0880***	0.1506***
$\widehat{h2}$: Oib(d-1)×Bignews (d)	0.3080***	0.5195***	0.4574**	1.4195***
$\widehat{h3}$: Oib(d-1)×NBignews (d)	-0.0185**	0.0044	0.0020	-0.0418**
N(observations)	744,705	131,276	415,656	951,793
Interquartile (Oib)× $\widehat{h1}$	0.1691%	0.0382%	0.0851%	0.1056%
Interquartile (Oib)× $(\widehat{h1}+\widehat{h2})$	0.7326%	0.6794%	0.5272%	1.1010%
Interquartile (Oib)× $(\widehat{h1}+\widehat{h3})$	0.1353%	0.0437%	0.0870%	0.0763%
Contribution of Bignews days (3.65%)	14.91%	39.17%	18.90%	30.22%
Contribution of NBignews days (30.62%)	23.10%	21.14%	26.17%	17.57%

Table IA3 Robustness checks for stock return prediction and firm-level news

This table presents robust results on investors' stock return predictive power. The sample period is from January 2016 to June 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month and we match these stocks with the investors' trading information. First, we add firm event dummy variables as independent variables into equation (IA1) and report the regression results in Panel A. Second, we repeat the analysis with media news from CNRDS and present results in Panel B. In Panel C, we separate all events into earnings announcement and analyst activities, as shown in equation (IA6),

$$\text{(IA6)}\quad Ret(i,d) = h0(q,G) + [h1(q,G) + h2(q,G)BignewsEarn(i,d) + h3(q,G)NBignewsEarn(i,d) + h4(q,G)BignewsAnalyst(i,d) + h5(q,G)NBignewsAnalyst(i,d)] \times Oib(i,d-1,G) + h6(q,G)'Controls(i,d) + \epsilon(i,d,G),$$

where *BignewsEarn(i, d)* is equal to one if stock *i*'s return on earnings day *d* is outside the 5th and 95th percentiles of earnings day return in quarter *q-1*, otherwise it is zero. *NBignewsEarn(i, d)* is equal to one if stock *i*'s return on earnings day *d* is within the 5th and 95th percentiles of earnings day return in quarter *q-1*, otherwise it is zero. *BignewsAnalyst(i, d)* is equal to one if stock *i's* return on analyst activity day *d* is outside the 5th and 95th percentiles of analyst-related day return in quarter *q-1*. *NBignewsAnalyst(i, d)* is equal to one if stock *i*'s return on analyst activity day *d* is inside the 5th and 95th percentiles of analyst-related day return in quarter *q-1*. In Panel D, we directly examine whether foreign investors have greater return predictive power on days when stock prices experience large movements, as specified in equation (IA7),

$$\text{(IA7)}\quad Ret(i,d) = l0(q,G) + [l1(q,G) + l2(q,G)Bigday(i,d)] \times Oib(i,d-1,G) + l3(q,G)'Controls(i,d-1) + \epsilon(i,d,G)$$

where the indicator variable *Bigday(i, d)* is equal to one if the return for stock *i* on day *d* is outside the 5th and 95th percentile of sample returns in quarter *q-1*, otherwise it is zero. All dependent variables are expressed in percentages. *Adj-*R^2 is the time-series average of the adjusted R-squared in the cross-sectional regression. *N(observations)* is the number of observations in the regressions. Control variables are same as those in equation (3). The standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. To save space, we omit coefficients on control variables and *t*-statistics in the table and report the number of observations. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Firm event dummy variables for earnings announcement and analyst activities

Dep: Ret(d)	1	2	3	4
	QFII	RQFII	HKC	Local INST
Oib(d-1)	0.0967***	0.0425**	0.0945***	0.1767***
Oib(d-1)×Bignews(d)	0.5074***	0.5951**	0.3896*	2.2696***
Oib(d-1)×NBignews (d)	-0.0335**	0.0126	0.0417	0.0206
Bignews(d)	1.1202*	1.1870*	1.1627*	0.7830*
NBignews(d)	0.2306***	0.2454***	0.2487***	0.2284***
Adj-R^2	1.28%	1.79%	1.45%	1.17%
N(observations)	744,205	131,279	415,656	951,793

Panel B. Firm event dummy variables for media news

Dep: Ret(d)	1	2	3	4
	QFII	RQFII	HKC	Local INST
Oib(d-1)	0.0936***	0.0343*	0.0904***	0.1513***
Oib(d-1)×Bignews(d)	0.3143**	0.2668***	0.3704	1.3388***
Oib(d-1)×NBignews (d)	-0.0157*	0.0061	0.0013	-0.0259
Bignews(d)	1.4882**	1.2657**	1.2245*	1.3121**
NBignews(d)	0.1420***	0.1045***	0.1222***	0.1622
Adj-R^2	3.89%	3.93%	3.85%	3.45%
N(observations)	744,705	131,276	415,656	951,793

Panel C. Separate earnings announcements and analyst activities

Dep: Ret(d)	1	2	3	4
	QFII	RQFII	HKC	Local INST
Oib(d-1)	0.0968***	0.0423**	0.0934***	0.1782***
Oib(d-1)×BignewsEarn(d)	0.1866	0.8202	0.1450	0.3953
Oib(d-1)×NBignewsEarn (d)	-0.0142	-0.1057	0.0813**	-0.1358***
Oib(d-1)×BignewsAnalyst (d)	0.3336***	0.6139**	0.2204	2.8575***
Oib(d-1)×NBignewsAnalyst (d)	-0.0374***	0.0401	0.0954*	0.0546***
Adj-R^2	0.77%	1.21%	0.68%	0.75%
N(observations)	744,205	131,279	415,656	951,793

Panel D. Large stock price changes

Dep: Ret(d)	1	2	3	4
	QFII	RQFII	HKC	Local INST
Oib(d-1)	0.0626***	0.0255**	0.0658***	0.0730***
	(7.09)	(2.10)	(3.46)	(3.58)
Oib(d-1)×Bigday(d)	0.3697***	0.3907***	0.4548***	1.1838***
	(3.78)	(2.94)	(3.10)	(12.62)
Adj-R^2	1.06%	1.20%	0.80%	1.10%
N(observations)	787,197	143,723	444,489	1,007,350

Table IA4 Market-level information environment indicators

Panel A. Definition

Measures	Description
Prevalence of foreign ownership(World Economic Forum, 1 = extremely rare; 7 = extremely prevalent)	Response to the survey question “In your country, how prevalent is foreign ownership of companies?”
The extent of shareholder rights index (World Bank, 0=less rights to more rights)	The extent of shareholder rights index measures the role of shareholders in key corporate decisions. It has six components: (i) whether the sale of 51% of Buyer's assets requires shareholder approval; (ii) whether shareholders representing 10% of Buyer's share capital have the right to call for a meeting of shareholders; (iii) whether Buyer must obtain its shareholders' approval every time it issues new shares; (iv) whether shareholders automatically receive preemption rights when Buyer issues new shares; (v) whether shareholders elect and dismiss the external auditor; (vi) whether changes to the rights of a class of shares are only possible if the holders of the affected shares approve.
Strength of auditing and accounting standards(World Economic Forum, 1=extremely weak to 7=extremely strong)	Response to the survey question “In your country, how strong are financial auditing and reporting standards?”

Panel B. List of emerging markets

Index	Emerging Markets	Index	Emerging Markets
1	Brazil	11	Philippines
2	Chile	12	Poland
3	Colombia	13	Russia
4	Egypt	14	Saudi Arabia
5	Greece	15	South Africa
6	Hungary	16	Taiwan
7	India	17	Thailand
8	Indonesia	18	Turkey
9	Malaysia	19	UAE
10	Mexico		

Table IA5 Further decomposition on investors' account performance

This table presents the account performance of foreign investors as well as local institutions. Our sample period is from January 1, 2016, to June 30, 2019. Our sample includes common stocks with at least fifteen non-zero volume trading days in the previous month and we match these stocks with the investors' trading information. We separate account performance on day *d* into three parts, as shown in equations (IA8) and (IA9) below.

(IA8) $StkSelect(d,G) = HoldingPerformance(d) + TransactionGains(d) + OrderImbalanceGains(d)$

(IA9) $HoldingPerformance(d,G) = \sum_{i=1}^{N} HoldShares(i,d-2,G) * close(i,d-1) * [Ret(i,d) - MktRet(d)]$,

$TransactionGains(d,G) = \sum_{i=1}^{N} BuyShares(i,d,G) * BuyPrice(i,d,G) * [Ret(i,d) - MktRet(d)] - \sum_{i=1}^{N} SellShares(i,d,G) * SellPrice(i,d,G) * [Ret(i,d) - MktRet(d)]$,

$OrderImbalanceGains(d,G) = \sum_{i=1}^{N} [BuyShares(i,d-1,G) - SellShares(i,d-1,G)] * close(i,d-1) * [Ret(i,d) - MktRet(d)]$.

Take stock selection as an example. The first part *HoldingPerformance* represents gains from stock holdings preceding day *d-1*. The second part *TransactionGains* represents the gains from transactions on day *d*. The final part *OrderImbalanceGains* represents gains from trading on day *d-1*, which tracks the performance from one-day return prediction of order flows. Panels A and B, present the decomposition results for stock selection and market timing, respectively.

Panel A. Separation on stock selection performance

Investor	Stock selection (%)	Holding Gain(%)	Transaction Gain(%)	Order Imbalance Gain(%)
QFII	20.76%	20.73%	-0.15%	0.18%
RQFII	23.40%	23.65%	-0.22%	-0.03%
HKC	20.84%	20.54%	0.02%	0.29%
Local INST	14.04%	14.06%	-0.26%	0.24%

Panel B. Separation on market timing performance

Investor	Market Timing (%)	Holding Gain(%)	Transaction Gain(%)	Order Imbalance Gain(%)
QFII	-3.61%	-4.01%	0.32%	0.08%
RQFII	-2.63%	-2.82%	0.16%	0.03%
HKC	-0.69%	-1.39%	0.52%	0.18%
Local INST	-3.16%	-3.44%	0.26%	0.03%

Figure IA1 The time-series coefficients of the order imbalance in the next day's return prediction

In equation (3), we use the Fama-MacBeth regression to examine investors' predictive power on the next day's stock return. We plot the time-series coefficients on the previous day's order imbalance in the first-stage regression.