Are Foreign Investors Informed?
Trading Experiences of Foreign Investors in China

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ABSTRACT

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Keywords: Foreign investors, the Chinese stock market, public information, market liberalization.
JEL classification: G12, G14, G15, G18.

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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, foreigners facilitate cross-border mergers and acquisitions (Ferreira, Massa and Matos, 2010), promote corporate governance (Ferreira and Matos, 2008; Aggarwal et al., 2011), expedite global information transmission (Bae et al., 2012), and improve price efficiency (Kacperczyk, Sundaresan and Wang, 2021). Over the past 20 years, regulators from China, clearly recognizing these benefits, 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 the domestic A-share stock market. First, the Qualified Foreign Institutional Investors (QFII) program, launched in November 2002, allowed 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, permitted qualified overseas institutional investors to invest directly in the domestic capital market using offshore RMB. Third, and most recently, the Hong Kong Stock Connect (HKC) program, linking the Shanghai Stock Exchange (SSE) and the Hong Kong stock market, was launched in November 2014. HKC enables Hong Kong and overseas individual and institutional investors to trade eligible stocks listed on the SSE.[1] By the end of 2021, foreign investors held around RMB 3.67 trillion in A-shares through these various channels, collectively accounting for 4.97% of A-share aggregate market capitalization.[2]

Despite the rapidly growing presence of foreign investors in China, physical and language barriers remain. Hence, it is natural to ask whether these investors can process Chinese local

[1] The Shenzhen Stock Exchange initiated a similar connect program with Hong Kong Stock Exchange in December 2016.
[2] http://www.csrc.gov.cn/csrc/c100028/c1556036/content.shtml

market information and whether their trades can predict future price movements. In other words, we are interested in two questions: first, whether foreign investors are informed about future local stock returns, and second, if they are informed, what types of information - firm-specific, market-level or global are they better able to process. On the first question, the previous literature provides evidence against foreign investor informational advantages. Given the language and culture differences and the distances between foreign and local markets, several studies show that foreign investors are at a disadvantage when trading in local markets. For instance, Kang and Stulz (1997) find that foreign ownership in Japan does not predict future stock returns; Choe, Kho and Stulz (2005) show that foreign investors pay higher transaction costs than domestic money managers in South Korea; and Dvořák (2005) finds that foreign investors earn lower profits than local investors in Indonesia. In the context of the rapidly growing Chinese stock market, are foreign investors capable of processing information such that their trading activity predicts future Chinese stock returns? Will the patterns be similar to those findings for other emerging markets? If they are different, what types of information are particularly relevant? Answers to our research questions are interesting and important for the international investment community.

We are grateful that the Shanghai Stock exchange for sharing a comprehensive sample of investors' daily trading records from 2016 to 2019. For compliance purposes, the exchange identifies each buy and sell order with the originators and their access channels such as QFII, RQFII or HKC. Based on trade level information, we aggregate foreign orders flows at the stock level each day. For comparison purposes, we also collect order flows from local institutions, such as mutual funds, hedge funds, and others, to serve as a benchmark.

We first examine whether foreign investors are informed by measuring the link between their order flows and future stock price movement in the China A-share market. We find that foreign order flows from all three channels have significant predictive power for future stock returns. Taking QFII as an example, an interquartile increase in daily QFII order flow is associated with a 11.88 bps increase in the next day stock return (or 29.70% annualized), with a highly significant *t*-statistic of 17.02. When we turn to RQFII and HKC, an interquartile increase in daily RQFII and HKC order flows are associated with 3.05 bps and 7.57 bps increases in the next day return (or 7.63% and 18.93% annualized), respectively. For comparison, an interquartile increase in daily local institutional order flow is associated with a 9.33 bps increase in the next day return (or 23.33% annualized). Taking these figures together, foreign investors' trading activity predicts future local stock returns, and thus they seem to be informed about relevant fundamental information in China. Further, their predictive power is on par with their local institutional counterparts. Across these groups, the QFII order flows have the highest predictive power, even higher than the local institutions, while the RQFII has the lowest. The growing group of HKC investors exhibit similar predictive power with that of the local institutions. When we extend the prediction window from days to weeks, foreign investors still predict cumulative stock returns over longer horizons, implying that the information they have is not transient.

Given our evidence on return predictability, a natural next question is what types of information drive foreign investors' return prediction? Notice that information can be separated into different categories: firm-level vs. market-level and local vs. global. The prior literature shows that the physical distances and language barriers make it difficult for foreign investors to process local firm-level news. However, we find that this does not seem to be the case for foreign investors in China. There is clear evidence that foreign investors can process local firm-level information, in the sense that the predictive power of foreign investor order flows is, relative to non-event days, significantly higher on days with earnings announcements, analyst recommendations and media news. To be specific, the earnings and analyst-related significant news-days account for 0.49% of the total sample days, but they contribute to around 3.06%, 7.38%, and 1.94% of the overall predictive power of QFII, RQFII, HKC order flows, respectively. For comparison, these days account for 5.83% of local institutions' overall predictive power, comparable to that of the foreign investors. To explain these findings, it is possible that these foreign investors are stationed in or close to China and that they possess necessary language processing skills (or they hire somebody who does).

On the other hand, prior studies also propose that foreign investors might be capable of processing market-level news. For instance, Bae et al. (2012) find that stocks with a high degree of foreign investability are associated with a reduced price delay to global market information, indicating that foreign investors have an advantage in processing global market news. Perhaps foreign investors also have better access to global market news. Is that also true in China? Here, we use local and global market returns as proxies for market-level information. We provide suggestive evidence that the predictive power of foreign investors can be higher when the global market experiences large price movements, indicating that they may have abilities in processing the global market level information to some extent. However, the magnitude and significance of foreign investors' predictive power on market-level news days are much lower than those for firm-level news days, indicating that foreign investors in China might only have a limited advantage in processing market-level information.

Finally, for our four-year sample, Chinese regulatory authorities gradually relax the restrictions on foreign capital, allowing better access for foreign investors to participate in the Chinese stock market. For instance, they increase investment quotas in 2016, relax capital flow controls in 2018, and lift asset allocation limitations in 2019, etc. While these measures increasingly permit inflows of foreign capital, does the broader participation of foreign investors improve their overall predictive power regarding future stock returns? This becomes an interesting empirical question. On one hand, if the friendlier regulatory environment attracts more informed and active investors, then the predictive power of foreign order flows would increase. On the other hand, if the liberalization attracts less informed investors (say, index funds at one extreme), then the predictive power that we document might decrease. Our empirical results show that expanding investment quotas and capital flows improve foreign investors' return predictive power in general.

Our study is related to three strands of the previous literature. The first examines whether foreign investors face informational disadvantages in the local equity market. In addition to Kang and Stulz (1997) and Choe, Kho and Stulz (2005) mentioned earlier, Froot and Ramadorai (2008) suggest that the positive relationship between international portfolio flows and closed-end fund performance is linked to fundamentals. Ferreira et al. (2017) find that although foreign institutional ownership predicts local stock returns, the predictability is more consistent with a price pressure explanation rather than a reflection of underlying fundamentals. As these studies do not examine how foreign investors behave around specific types of information, there is little direct evidence on what types of information foreign investors are informed, especially in comparison with local investors.

A second strand of the literature contains studies on how foreign investors behave in the Chinese stock market. Chen, Wang and Zhu (2019) investigate the information content of net inflows from the HKC program. They find that HKC weekly net flows can predict stock returns, earnings surprise, and firm profitability. Besides, they suggest that foreign inflows may contain private information of mainland insiders who pretend to be foreign investors. Bian et al. (2020) find that equity flows via HKC on A-share stocks are negatively associated with stock volatility and help narrow valuation differentials between China A- and H-share markets.[3] Our study differs from these studies in two aspects. First, instead of focusing only on HKC, we investigate the performance patterns among all three foreign investor groups. We also compare foreign investors with local institutions to better understand foreign investors' informational advantages. Second, we dedicate ourselves to the source of foreign investors' predictive power using a broad scope of public information at both firm and market levels, which has not been extensively studied in previous research.

Finally, the third strand of literature concerns 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. However, given geographic distance and potential linguistic and cultural barriers, whether foreign investors can correctly process public information in a manner commensurate with local institutions remains unclear. By separating foreign investors from local institutions, our study delves deeper into the heterogeneity among institutional investors.

Compared with previous studies, our paper makes three distinct contributions. First, we are one of the few studies that provide comprehensive evidence on whether foreign investors, QFII, RQFII and HKC, can predict returns in Chinese stock market, and whether there are differences among these groups of foreign investors delineated by these different access channels. Second, we

[3] Other research investigates topics beyond foreign investors' return predictive power, such as information asymmetry (Chan, Menkveld and Yang, 2008), corporate governance (Huang and Zhu, 2015), investors' reactions to analysts' recommendation (Jia, Wang and Xiong, 2017), firm disclosure (Yoon, 2021) and corporate activity (Ma, Rogers and Zhou, 2021).

provide an in-depth analysis of whether and how foreign investors' order flows are related to many layers of public information, firm or market and local or global. Third, we establish evidence that regulatory changes, which facilitate foreign investors' access, improve their predictive power on local stock returns. Our findings on the predictive patterns of various foreign investors and their information processing skills are important for academic researchers, industry practitioners and regulators alike.

II. Hypothesis Development

To guide our empirical analysis, we develop four main hypotheses regarding foreign investors' informativeness, their abilities to process public information and the influence of government regulations.

The first hypothesis is about whether foreign investors' trading predicts future local stock price movements. We measure foreign investors' behavior by their trading order flows, which are widely used in studies on retail investors (Kelley and Tetlock, 2013; Barrot, Kaniel and Sraer, 2016; Boehmer et al., 2021) and institutions (Hendershott, Livdan, and Schürhoff, 2015). If order flows from a particular group of investors significantly predict future stock returns, we infer that this group of investors are informed, and vice versa. That is, if the foreign investors' order flows can predict future local stock returns, then these foreign investors are considered to be "informed".

The literature provides mixed evidence on the degree to which foreign investors are informed in the local market. On the one hand, in comparison with local investors, foreign investors are physically further away from local firms and might possess poorer information sources. It is also harder to maintain relationships with local firms and analysts. Therefore, as documented in Brennan and Cao (1997), Choe, Kho and Stulz (2005), Dvořák (2005), Agarwal et al. (2009), Baik et al. (2013), etc., foreign investors might not be informed about local firms, or at least they are less informed than local investors. On the other hand, foreign investors are generally institutions from more developed markets. These high-powered and well-resourced institutions might have considerable advantages in information collection and processing skills. Thus, as documented in Seasholes (2000), Grinblatt and Keloharju (2000), Bailey, Mao and Sirodom (2007), Froot and Ramadorai (2008), they are likely to be informed, even in an overseas market.

Based on previous findings, we propose our first hypothesis regarding the relationship between foreign investors' order flows and future stock returns in two versions:

Hypothesis 1a: Foreign investors from the QFII, RQFII, and HKC programs are informed about stock prices in the Chinese stock market; that is, their order flows can predict future stock returns.

Hypothesis 1b: Foreign investors from the QFII, RQFII, and HKC programs are not informed about stock prices in the Chinese stock market; that is, their order flows cannot predict future stock returns.

If some investors are informed about future stock price movements, it is normally the case that they are informed about either firm-specific or market-wide developments in a manner better than the general market such that they trade in a way that benefits them when that information is released. Therefore, we develop our second hypothesis regarding how foreign investors handle information. Since we don't have the means to measure private information, we focus on available public information data. Notice that public information is "private" before its public release, and one could be informed about eventually released public information, which is still a "private" information advantage.

We separate public information into three categories: firm-level information, local market-level information, and global market-level information. Given that all firms in our sample are Chinese firms, we first restrict our attention to local firm-level information. Previous literature shows that firm events such as earnings announcements and analyst activities contain valuable fundamental information, and stock prices normally exhibit a strong reaction to these releases (Bradley et al., 2014; Savor and Wilson, 2016). Therefore, if investors' return predictive power is related to their access and ability to process firm-level information, they should predict returns to a greater degree on firm-level news days (Hendershott, Livdan, and Schürhoff, 2015). Specifically, their order flows ahead of firm news should have greater return predictive power on firm-level news days than on non-news days.

Geographic distance can cause information asymmetry among investors, and investors located near their investment possess informational advantages (Hau, 2001; Coval and Moskowitz, 2001; Teo, 2009). Due to the physical proximity and the potential language and cultural barriers, it might be challenging for foreign investors to process local firm information. For instance, Jia, Wang and Xiong (2017) suggest that foreign investors in Hong Kong underreact to local analysts' recommendations on A-shares compared to local investors in Mainland China. If foreign investors are not able to process local firm news, we expect lower return predictive power on firm news days than on non-news days. Overall, we establish our second hypothesis regarding local firm-level information:

Hypothesis 2a: Foreign investors process local firm information relatively well. That is, the predictive power of foreign investors' order flows is higher on local firm news days than on non-news days.

Hypothesis 2b: Foreign investors are not able to process local firm information. That is, the predictive power of foreign investors' order flows is lower on local firm news days than on non-news days.

We next turn to market-level information, such as stock market movements and essential macroeconomic indicators announcements. Macro information has a significant impact on asset prices. Savor and Wilson (2014) show that assets earn much higher returns in the U.S. stock market on days when essential macroeconomic news is scheduled to be released. Given that many foreign investors in China are affiliated with the best investment institutions in the global market, it is possible that these investors can process market-level news, especially global news, better than their local counterparts. For instance, Bae et al. (2012), indicating foreign investors are advantaged in processing global information, show a high degree of foreign investors' 'investability' (meaning access) to emerging markets improves local stocks' price reaction to global information. Following the rationale developed above, if foreign investors are capable of processing market-level information, their return predictive power should be higher on market news days than on non-news days. On the other hand, market-level information, such as key economic indicator releases, is highly confidential. It may be much more difficult for foreign investors to access and respond prior to announcements. Overall, we establish our third hypothesis:

Hypothesis 3a: Foreign investors can process market-level news, especially global news. That is, the predictive power of foreign investors' order flows is stronger on market-level news days relative to non-news days, especially if it is news related to the global capital market.

Hypothesis 3b: Foreign investors are not able to process both local and global market-level news. That is, the predictive power of foreign investors' trade flows is weaker on market-level news days relative to non-news days.

Finally, we associate foreign investors' informativeness to market liberalization. Even though the Chinese regulators generally welcome foreign capital, they cautiously design the regulations through investment quotas, eligible stock pools and currency transfers to gradually facilitate foreign investors' participation. Given the previous literature's findings that market openness can lower firm capital costs (Bekaert and Harvey, 2000) and spur economic growth (Bekaert, Harvey and Lundblad, 2005), these restrictions are slowly modified over recent years to further improve market openness. How does this evolution relate to the degree to which foreign investors possess informational advantages in the local market? It is possible that 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. In contrast, we acknowledge that a friendlier investment environment could make it easier for less informed or passive investors to access the domestic stock market. We let the empirical results uncover which hypothesis fits the data better. We propose our fourth and final hypothesis regarding regulations:

Hypothesis 4a: The relaxation of restrictions on foreign investors improves their return predictive power in the Chinese stock market.

Hypothesis 4b: The relaxation of restrictions on foreign investors decreases their return predictive power in the Chinese stock market.

III. Institutional Background and Data

We provide institutional background on different types of foreign investors in Section III.A. In Sections III.B and III.C, we introduce the data and report summary statistics, respectively.

A. Foreign Investors in the Chinese Stock Market

Foreign investors can invest in the Chinese onshore stock market mainly through three liberalization programs: QFII, RQFII, and HKC. Launched in November 2002, QFII attracts foreign institutions especially long-term investors into Chinese domestic financial markets. Afterwards, to support RMB internationalization and facilitate Hong Kong as the offshore center for RMB-denominated business, RQFII was introduced in December 2011. Most recently, China initiated the HKC with the SSE in November 2014 and unveiled a similar program with the Shenzhen Stock Exchange (SZSE) in late 2016. HKC establishes mutual equity market access between Mainland China and Hong Kong and has quickly become an important passage for international capital. As investment channels for foreign capital, these three programs share common goals yet differ in several aspects, such as investor eligibility, investment scope and capital control, which may lead to distinctive performance patterns in the Chinese stock market.

We summarize the key differences in Table I. 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 oversea 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. In contrast, RQFII was created in 2011 to expedite offshore RMB business, and it was only available to Hong Kong subsidiaries of domestic security companies and commercial banks. Therefore, especially at its early stages, the RQFIIs include many institutions intending to attract offshore RMBs, rather than pursuing superior investment performance. For the HKC program, international asset management companies and overseas brokers backed by hedge funds are the main HKC investors. Retail trading accounts for only a small portion of the HKC program.[4]

Second, eligible stocks are different across the QFII, RQFII and HKC programs. QFIIs and RQFIIs are both allowed to 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 the SSE 180 Index and the SSE 380 Index, as well as all the SSE-listed A shares with H shares

[4] On April 19, 2021, Fang Xinghai, the vice chairman of CSRC, said on the BOAO Forum that, there are only three types of foreign investors through HKC: one is overseas retail investors, which account for small proportion; the second is overseas mutual funds, and other companies that engaged in global asset allocation; the third is overseas brokers backed by hedge funds.

listed on the Hong Kong Stock Exchange. The broad scope of financial instruments available for QFII and RQFII may attract large asset management companies who have multi-asset investment demand, as well as institutions that use derivatives to control risks or perform complex strategies. In addition, there are investment quotas on single QFII/RQFII/HKC investors, as well as certain aggregate restrictions across all program participants. To maintain the attractiveness of the Chinese stock market to foreign investors, the quotas are generally set at relatively high numbers (and are often not binding). To ensure that A-share stocks are not primarily owned by foreigners, 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.

Third, given government controls of cross-border cash flows, foreign investors are subject to capital controls. As mentioned earlier, QFIIs use foreign currency as principal, while RQFIIs use offshore RMB as principal. Meanwhile, for a long period, a QFII or RQFII investor must obtain a basic quota from the State Administration of Foreign Exchange (SAFE) that is no higher than a certain proportion of its assets under management. In terms of capital repatriation, QFIIs and RQFIIs were generally subject to a 3-month lock-up period, and QFIIs could only repatriate investment principal and profit 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 in short periods.

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 wider investment scope, QFIIs are likely to be sophisticated investors, focusing on long-term performance and fundamentals. In comparison, RQFIIs may be less sophisticated because many are Hong Kong subsidiaries whose primary goal is the absorption of offshore RMB. In contrast, HKC investors can trade more freely over short horizons which may or may not attract relatively informed investors. [5]

Over our sample period of 2016 to 2019, regulators gradually remove restrictions on quotas and capital controls. We summarize these changes in Figure 1. For instance, restrictions on capital repatriation for QFII and RQFII were removed in June 2018, and the investment quota was gradually increased and eventually lifted in May 2020. The process of market liberalization offers us a unique opportunity to examine the impact of liberalization on the evolution of foreign investors' behavior.

B. Data Sources

Our sample period spans January 1, 2016 to June 30, 2019. We obtain foreign investors' daily trading and holding information from Shanghai Stock Exchange, the largest stock exchange in China.[6] For each stock each day, we collect buy and sell data for different groups of foreign investors. Given that most of the foreign investors are institutional investors, we also collect information on local institutional investors to serve as a comparison benchmark.[7] 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 imbalances data to measure their trading activities. Following Jones et al. (2021), we compute investor group G's order imbalance for stock i on day d as follows:

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

[5] It is possible that some foreign institutions access the Chinese stock market through multiple programs. Clearly, pending approvals from Chinese regulators, sophisticated institutions might optimize over the three programs. This strategic approach is not the focus of our study, and we leave it to future research.
[6] We are grateful to the Shanghai Stock Exchange for data access.
[7] Since there are debates about whether HKC investors are true or faked foreign investors, CSRC declared on December 17, 2021, that trading from mainland investors only accounts for 1% of HKC's trade volume.

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 investors buy more than sell, and a negative number means that investors sell more than buy. The order imbalance variable is set to missing when there is no stock trading on that day.

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 the SSE data 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.

C. Summary Statistics

We present summary statistics of our key variables in Table II. Panel A reports the trade and holding data of foreign investors and local institutions. On average, QFII, RQFII and HKC investors hold 1,261, 901 and 744 stocks per day, respectively, covering more than half of the number of stocks in the Chinese A-share market. In terms of trading, QFII, RQFII and HKC investors trade 946, 174 and 561 stocks per day, indicating that QFIIs are more active than RQFIIs. The lower number of stocks traded by HKC is mostly a result of the investment constraints imposed by the regulators. For average daily trading volumes, QFII, RQFII, and HKC investors account for 0.79%, 0.08%, and 2.24% of market daily volume, respectively, and their holdings, for 0.95%, 0.23%, and 1.20% of market floating capitalization. The above results indicate that QFII and HKC investors are active in the Chinese stock market, whereas RQFII investors tend to trade less frequently. Local institutions also trade actively in the market. They hold and trade over 1,200 stocks per day, and their holdings account for 14.19% of market capitalization. Unlike developed markets, such as the U.S., the Chinese stock market is dominated by retail investors, and that's why all institutional investors, foreign and local, only account for about 20% of daily trading volumes.[8] We show how foreign investors' trading and holding magnitudes change over time in Figure 2. The trading volume and holdings of QFIIs and RQFIIs are relatively stable. HKC becomes considerably more important over time, with trading volume and holdings steadily increasing to become, by the end of our sample period, the largest foreign investor group among the three.

Since the focus of our study is on the cross-sectional trading behaviors of foreign investors, Table II 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, indicating substantial cross-sectional variation. The large cross-sectional variation in QFII and RQFII order flow may result from two facts: first, the number of these institutions is generally small in China; second, for one particular stock, the trades are likely concentrated in one direction, causing the order imbalance measure to take values close to 1 or -1. 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 are smaller than those of the foreign investors. The last column reports the cross-sectional mean of the first-order autocorrelation of the order imbalance measure. The coefficients

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[8] To better understand which stocks are more likely to attract foreign investors, we present in Table IA.I of Internet Appendix the daily trading volumes of foreign investors for firms with different characteristics. Foreign investors, as well as local institutions, tend to trade and hold stocks with larger size and higher earnings-to-price ratio. In Appendix A, we also directly examine which factors affect foreign investors order flows. We link investors' order flow with past returns, its own lag and other firm level characteristics. The results in Table IA.II show that foreign investors are daily contrarian investors (with a negative coefficient of order flow on the previous day returns), and their flow loads significantly on firm size, the earnings-to-price ratio, and the turnover ratio.

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.

To understand how the trade flows are related among different groups of investors, we present in Table II Panel C the time-series average of the cross-sectional Pearson correlation coefficients for order imbalance measures across four investor groups. The order imbalances of all investor 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 (correlation between QFII and HKC), indicating that investors' trading behaviors are different across groups.

IV. Empirical Results

In this section, we present our main empirical results. We examine whether foreign investors can predict future stock returns in Section IV.A. We connect foreign investors' predictive power with local firm-level information and market information in Section IV.B and IV.C, respectively. Finally, we investigate how regulation changes affect foreign investors' predictive power in Section IV.D.

A. Predicting Future Stock Returns

We examine Hypothesis 1 on whether foreign investors' trade flows can predict future stock returns in this section. We start with the next-day return prediction and then consider several longer-period return predictions. We also compare trading pattern differences between foreign investors and local institutions.

A.1. Predictive Power in Short Horizon

To investigate the short-term return predictive power of foreign order flows in the cross section, we adopt the two-stage Fama-MacBeth (1973) regression method. At the first stage, we estimate the following cross-sectional specification for each group *G* and each day *d*:

$$Ret(i,d) = a0(d,G) + a1(d,G)Oib(i,d-1,G) + a2(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \tag{2}$$

where 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 in our dataset. The main 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 the previous day's stock return $Ret(i,d-1)$, 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.

From the first stage estimation, we obtain a time-series of the cross-sectional coefficients $\{\widehat{a0}(d,G), \widehat{a1}(d,G), \widehat{a2}'(d,G)\}$. In the second stage, we compute means and standard errors, and conduct inference using the time-series of these coefficients. The standard errors are calculated using the Newey-West (1987) methodology with five lags, the optimal lag number under the Bayesian information criterion. If a particular group G of foreign investors' order flow correctly predicts future stock returns, we expect a significantly positive average coefficient $\widehat{a1}(G)$. An insignificant coefficient of $\widehat{a1}(G)$ indicates no predictive power, and a significant and negative coefficient $\widehat{a1}(G)$ implies that the foreign investors' trades are, on average, opposite to future stock price movements.

Table III Panel A presents the estimation results of equation (2). For QFII, the coefficient on Oib is 0.0649 (t-statistic=17.02), implying that QFII's order flow significantly and correctly predicts future stock returns. In terms of the magnitude, given the interquartile of QFII order flow is 1.8295, when we move from the 25th to the 75th percentile, the next day return increases by 1.8295*0.0649*0.01=0.1188% (29.70% annualized). 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% (7.63% and 18.92% annualized), respectively. The coefficient on Oib for local institutions is 0.1330 (*t*-statistic=18.57), and the daily interquartile return is 0.0933% (23.33% annualized). These results provide support to Hypothesis 1a that, on average, all three types of foreign investors' order flows correctly predict the next day's stock returns with interquartile returns comparable to one another.

We also examine whether the predictive power of foreign investors that we document is stronger or weaker than that exhibited by local institutions. Specifically, 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 coefficients $\widehat{a1}(d, G)$ 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 mean of time-series interquartile return differences between different foreign investors and the 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%*250day = 6.38% per year), with a *t*-statistic of 3.29. That is, the predictive power of the QFII order flows seems to be significantly higher than the local institutions. For the RQFII and HKC order flows, their predictive power is lower than local institutions, with daily differences in interquartile returns being -0.0626% and -0.0184%, respectively, also with high statistical significance. The simple comparison shows that QFII has the highest interquartile returns, local institutions the second, HKC the third, and RQFII the lowest.

In comparison with findings in the literature that foreign investors have limited informational advantages in Emerging East Asia, this result is surprising. For example, Froot, O'Connell and Seaholes (2001) find that foreign portfolio flows have insignificant predictive power on future equity returns at short and long horizons in markets such as Hong Kong, Indonesia, and Korea. Using Chinese market data from 2000-2010, Ferreira et al. (2017) show a portfolio sorted by local institutional ownership earns 0.65% (*t*-statistic=1.53) higher monthly excess returns than a portfolio sorted by foreign institutional ownership. In sharp contrast, we find, using comprehensive trading records, that foreign investors such as QFII perform better than local institutions, suggesting that they may, in fact, possess informational advantages in the Chinese stock market.

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. While 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^2s from the first-stage OLS regressions range from 8.83% to 14.75%. In Figure 3, we show the time-series coefficients $\widehat{a1}(d, G)$ to ensure that there are no outliers in the cross-sectional regressions over time. The time-series are stable and do not display extreme values.

A.2. Predictive Power over Longer Horizons

Given the strong one-day prediction for stock returns, we examine whether the predictive power remains over longer horizons. If so, it is likely that foreigners' predictive power is associated with firm fundamentals rather than with short-term microstructure effects, such as price pressure from order flows. For longer horizon predictions, we extend the Fama-MacBeth regression as follows:

$$Ret(i,w) = a0(d,G) + a1(d,G)Oib(i,d-1,G) + a2(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \tag{3}$$

Here the dependent variable $Ret(i,w)$ is the cumulative return over future w weeks after day d, 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. As in equation (2), we use the previous day's order imbalance as the main independent variable. If foreign investors' predictive power extends to longer horizons, we expect a positive and significant coefficient, $\widehat{a1}(G)$. The control variables are the same as those in equation (2). Standard errors are adjusted following Newey and West (1987) with five lags.

Table III Panel B presents the estimation results. To save space, we only report the coefficients on *Oib*. 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 is 0.1123 at week 1, and gradually increases to 0.2507 at week 12. All coefficients differ from zero at the 1% significance level, indicating that order flows from QFIIs can predict returns over longer horizons. The patterns are similar for RQFII and local institutions. For HKC, the coefficient climbs from 0.0985 at week 1 to 0.1874 at week 8, then declines to 0.1677 at week 12, indicating a slight price reversal. Overall, foreign investors across these various programs predict returns over longer periods, indicating that their return predictive power may be related to fundamental information instead of price pressure.

To understand 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 4. We observe the following three patterns. First, all four lines trend up and do not present major reversals over 12 weeks, confirming the results in Table III Panel B that the predictive power of foreign and local institutions' order flows are lasting rather than transient. Second, the interquartile returns for QFII and local institutions are quite close to each other, while both are larger than that of RQFII and HKC over the next 12 weeks. From the bottom of Table III and Panel B, their performance is similar and does not exhibit statistically significant differences over the longer horizon of 12 weeks. Third, starting from week 2, RQFII performs better than HKC over longer horizons.[9]

The above three patterns show that QFII's long-term performance closely match that of local institutions, echoing the results for short-term predictions. Meanwhile, foreign investors' performance differences may be related to their institutional background. As QFII has the strictest eligibility requirements, 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.

[9] In the Internet Appendix B and Table IA.III, we show similar predictive patterns when using risk adjusted returns.

A.3. Overlapping and Specific Order Imbalance

Our results thus far imply that foreign investors, such as QFII, perform similar to local institutions. It is possible that foreign and local investors share overlapping information, so that they then trade similarly, leading to similar predictive patterns. It is also possible that they possess different information, and they have 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 recheck 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,

$$Oib\left(i, d, G_{Foreign}\right) = b0(d, G) + b1(d, G)Oib(i, d, G_{Local}) + \epsilon(i, d, G). \tag{4}$$

After we obtain the time-series of $\widehat{b1}(d, G)$, we decompose the foreign order flow into two parts,

$$\begin{aligned} Oib_{i,d,G_{Foreign}}^{overlap} &= \widehat{b1}(d, G)Oib(i, d, G_{Domestic}), \\ Oib_{i,d,G_{Foreign}}^{specific} &= \widehat{b0}(d, G) + \hat{\epsilon}(i, d, G), \end{aligned} \tag{5}$$

with the first term being the overlapping component, and the second term being the foreign-specific component.[10] We also decompose local institutions' order imbalance following a similar procedure, where the dependent variable is the local institutions' order imbalance and independent variables are order flows from all three foreign investor groups.

To find out whether it is the overlapping component or the specific component that drives the predictive power, we estimate the following Fama-MacBeth (1973) regression for each day:

$$Ret(i, d) = a0(d, G) + a1(d, G)Oib_{i,d-1,G}^{overlap} + a2(d, G)Oib_{i,d-1,G}^{specific} \tag{6}$$

[10] To save space, we provide additional detail on the calculation in Internet Appendix C and report the parameter estimates in Table IA.IV. The coefficients $\widehat{b1}$ are mostly positive, suggesting that foreign investors' order flows move in the same direction as the local institutions' order flows to some degree.

$$+a3(d,G)'Controls(i,d-1)+\epsilon(i,d,G)$$

Positive coefficients $\widehat{a1}(G)$ and $\widehat{a2}(G)$ indicate that both overlapping and specific order imbalances contribute to the order flows' predictive power for future stock returns. The control variables are the same as those in equation (2).

Table IV reports the estimation results. For QFII, the coefficients on $Oib^{overlap}$ and $Oib^{specific}$ are 0.3553 and 0.0593, with *t*-statistics of 0.18 and 15.67, respectively, indicating that QFII's predictive power mostly stems from unique 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 performance. Similar patterns are observed for RQFII, HKC, in the sense that only the foreign specific order imbalance displays significant return predictive power. In contrast, the pattern is different from that which we observe for local institutions, where both 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.

Our findings that foreign-specific order flows contribute more to foreign investors' return predictive power, especially for QFII, suggest that foreign investors may possess unique informational advantages in the local stock market. These may reflect foreign investors' ability to correctly process local information. Given this finding, we next turn to an examination of the types of information, firm-level vs. market-level and global vs. local, that are behind the predictive patterns of order flows of foreign and local investors that we observe.

B. Firm Information and Return Predictive Power

Investors' return predictive power may stem from their access and processing skills of both public and private information. In this section, we test Hypothesis 2 by investigating whether foreign investors are informed about local firm information and exhibit greater return predictive power on relevant public information days. Section IV.B.1 focuses on firm events related to earnings announcements and analyst activity. Section IV.B.2 considers media-related news.

B.1. Earnings Announcements and Analyst-related Activity

The prior literature reveals that earnings announcements and analyst-related activities are related to firm fundamentals and have implications for future stock price movements (Bradley et al., 2014; Savor and Wilson, 2016). We obtain earnings announcement data from WIND. For analyst data, though CSMAR is a widely used analyst database (Dong et al., 2021; Chen et al., 2022), its coverage is incomplete particularly in earlier periods (Li, Wong and Yu, 2020). Following Li, Wong and Yu (2020), we construct a comprehensive analyst sample from four major data providers: CSMAR, WIND, RESSET, and SUNTIME. [11] For analysts' activities, we focus on forecast revisions and recommendation changes. Because analyst forecasts and recommendations overlap at the stock-day level, we combine the two activities together as analyst-related events. Our sample includes 15,477 earnings announcements and 41,722 analyst-related events, totaling 50,331 event days for individual stocks, accounting for 4.94% of all stock-days in our sample.

Since these firm events contain valuable fundamental information, stock prices normally exhibit strong reactions to the news. If investors can access, or anticipate the information contained therein, their order flows ahead of events should have greater return predictive power on event days than non-event days, which would be consistent with Hypothesis 2a. Given the geographic,

[11] The dataset construction details are provided in the Internet Appendix D.

language, and culture barriers, foreign investors may be disadvantaged in accessing or processing local firm information. Regarding Hypothesis 2b, in this case, we expect that the predictive power of foreign investors is lower on firm event days than on non-event days.

Notice that some news is fully expected, and hence leads to no reaction in realized returns, whereas other news items are unexpected and lead to large reactions in returns. Hence, the stock price change is an intuitive measure of the importance of firm events (Ivković and Jegadeesh, 2004; Savor, 2012; Jiang and Zhu, 2017). For instance, Ivković and Jegadeesh (2004) find the largest stock price reactions to analyst upgrade recommendations a week before the earnings announcements date, suggesting a sharp increase of information content. Jiang and Zhu (2017) use large stock price jumps to identify significant information events. Motivated by these studies, we first compute the 5th and 95th percentiles of event day returns across all firms and all days to separate the largest reactions of returns to the information, which also indicates that these events are most value relevant. We define an indicator $Tail(i,d)$, which is equal to 1 if stock i's return on event day d is outside of these 5th and 95th percentiles, and otherwise it is zero. Similarly, we define another indicator, $NTail(i,d)$, which is equal to 1 if on event day d, stock i's return is within the 5th and 95th percentiles, and otherwise it is zero.

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:

$$\begin{aligned} Ret(i,d) &= a0(d,G) \\ &\quad + [a1(d,G) + a2(d,G)\,Tail(i,d) + a3(d,G)NTail(i,d)] \\ &\quad \times Oib(i,d-1,G) + a4(d,G)'Controls(i,d) + \epsilon(i,d,G). \end{aligned} \tag{7}$$

Here, investors' order flows interact with the two indicators to allow the predictive power to differ on the most and least value-relevant events. If the next day is a non-event day, $a1(G)$ captures the predictive relation between order flows and future returns. If the next day is an event-day with large movements in prices, $a1(G) + a2(G)$ captures the predictive relation between order flows and future returns. Similarly, if the next day is an event-day but not with large movements in prices, $a1(G) + a3(G)$ captures the predictive relation between order flows and future returns. Positive coefficient estimates, $a2(G)$ and $a3(G)$, indicate that investor group G has higher return predictive power on event days than on non-event days, suggesting that investors can process firm information regardless of the content quality. The differences in coefficients, $a2(G)$ and $a3(G)$, tells us whether the investors are able to process information related to large price movements or not. Notice that earnings announcements and analyst recommendations are not evenly distributed over calendar days, so we estimate the first-stage regression for every calendar quarter to ensure sufficient variation in our event dummy variables. All controls are the same as those in equation (2) and the standard errors are calculated using Newey-West's (1987) methodology with five lags.[12]

Table V presents the estimation results for equation (7). For QFII, the $\widehat{a1}$, $\widehat{a2}$ and $\widehat{a3}$ coefficients are 0.0977, 0.5177 and -0.0342 respectively, all significant at the 99% confidence level. The interquartile return on non-event days is 0.0977*1.8295*0.01=0.1787%, the interquartile return on event days with large price changes is (0.0977+0.5177)*1.8295*0.01=1.1259%, and the interquartile return on event days with small price changes is (0.0977-0.0342)*1.8295*0.01=0.1161%. That is, the predictive power of QFII for future stock returns are quite similar before non-event days and event days with no large price changes, while before event

[12] We consider two alternative specifications for firm level earnings news. To save space, we include them in the Internet Appendix. First, we separate the earnings news and analyst news in Internet Appendix E and Table IA.V. We find both foreign investors and local institutions are more capable of processing analyst-related events rather than earnings announcements. Second, to maintain ease of interpretation in the main text, we do not add dummy variables. In the Internet Appendix F and Table IA.VI and Table IA.VII, we show that inclusion of event dummy variables does not change any findings in Section IV.B.

days with large returns, their predictive power is almost six times higher. These results show that QFIIs can anticipate or have access to firm information when the most value-relevant news become public on 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. Overall, these results support Hypothesis 2a, as we find that foreign investors are capable of processing local firm information related to earnings announcements and analyst activity, especially regarding events leading to large price movements.

Following Boehmer et al. (2020), we also gauge the importance of firm events to investors' overall performance using the fact that 0.49% of the sample are events with large price changes and 4.45% of the sample are events with small price changes. Take QFII, for example. The overall performance is the sum of interquartile returns on event days multiplied by the percentage of event days in the total sample, calculated as follows:

0.1787%*(1-4.94%)+1.1259%*0.49%+0.1161%*4.45%= 0.1806%.

Event days with large price changes account for (1.1259%*0.49%)/0.1806%=3.06% of the overall performance, and event days with small price changes account for (0.1161%*4.45%)/0.1806%=2.86%. Similarly, the contribution of the most valuable event days for RQFII, HKC and local institutions is 7.38%, 1.94% and 5.83%, and the contribution of least valuable event days is 6.73%, 7.87%, and 4.13%, respectively. Except for HKC, the most valuable events contribute much more to overall performance than the least valuable events. The results indicate that events with large price changes are important sources of investors' return predictive power.[13]

B.2. Media News

The previous literature also shows that press coverage contains uncovered content regarding firm's fundamentals that can be used to predict future stock returns (Tetlock, Saar-Tsechansky and Macskassy, 2008). In this section, we collect news data from the Chinese Research Data Service Platform's Financial News Database of Chinese Listed Companies (CFND). CFND gathers financial news from over 400 websites and 600 newspapers, including reports from 20 mainstream online financial media outlets and China's eight largest national business newspapers, all written in Chinese. Using the same database, Ge and Zhang (2022) show that the news tone can correctly predict stock returns in both short and long horizons, implying that news contains valuable information on stock prices. Our sample contains 353,551 firm-news days, accounting for 34.69% of total observations.

Similar to equation (7), we estimate the following Fama-MacBeth regression:

$$\begin{aligned} Ret(i,d) = a0(d,G) + [a1(d,G) + a2(d,G)TailNews(i,d) + \\ a3(d,G)NTailNews(i,d)] \times Oib(i,d-1,G) + a4(d,G)'Controls(i,d-1) + \\ \epsilon(i,d,G). \end{aligned} \tag{8}$$

The difference between equation (7) and (8) is the definitions for the two indicators, $TailNews(i,d)$, and $NTailNews(i,d)$. For equation (7), we focus on earnings and analyst news, and these indicators are based on the 5^{th} and 95^{th} percentiles of all event day returns. For equation

[13] We further separate large price movement firm event days into positive return days and negative return days, and present the findings in Internet Appendix G and Table IA.VIII, We find that investors tend to have higher return predictive power on days with negative returns.

(8), we compute the 5th and 95th percentiles of all media news day returns. That is, $TailNews(i, d)$ is equal to 1 if stock i's return on news day d is outside the 5th and 95th percentiles of all news day returns and otherwise it is zero, and $NTailNews(i, d)$ is equal to 1 if stock i's return on news day d falls within the 5th and 95th percentiles, and otherwise it is zero. We focus on the coefficients of the interactions with the previous day's order imbalance. Positive coefficients, $\widehat{a2}(G)$ and $\widehat{a3}(G)$, mean that foreign investors are informed about news content. We perform quarterly Fama-MacBeth regressions to guarantee enough variation on news dummy variables.

Table VI presents the estimation results of equation (8). Take QFII as an example. The $\widehat{a1}$, $\widehat{a2}$ and $\widehat{a3}$ coefficients are 0.0906, 0.3550 and -0.0085 respectively. All except $\widehat{a3}$ are significant at the 99% confidence level. The interquartile return on non-news days is 0.0906*1.8295*0.01=0.1657%, the interquartile return on news days with large price changes is (0.0906+0.3550)*1.8295*0.01=0.8153%, and the interquartile return on news days with small price changes is (0.0906-0.0085)*1.8295*0.01=0.1502%. The results suggest that order flows from QFIIs have predictive power for future stock returns, especially for news days with large price movements. However, for RQFII and HKC, we find insignificant coefficients on the interactions, indicating that their predictive powers are not significantly different on media news days. The predictive power of local institutions' order flows is significant on no-news days and much higher on news days, but not on news days without large price movements. While comparing different groups of investors, we find the order flows from all foreign investors and local institutions have stronger predictive power when there are significant media news on the next day, indicating that they may have access to the news before it is announced, or they can anticipate the news. The coefficient is significant for QFII and local institutions, but not for RQFIIs and HKC investors.

We also present the contribution of public firm news to investors' performance, following the same decomposition procedure in the previous section. Given that news days with large and small price movements make up 3.47% and 31.23% of total observations respectively, we calculate overall performance for QFII as 0.1657%*(1-34.69%)+0.8153%*3.47%+0.1502*31.23%=0.1834% daily. News days with large price movements contribute (0.8153%*3.47%)/0.1834%=15.42% to overall performance, and news days with small price movements contribute (0.1502*31.23%)/0.1834%=25.57%. For RQFII, HKC, and local institutions, news days with large price movements contribute 22.53%, 8.18%, and 26.61% to the overall performance, respectively. The results imply that financial media news associated with large price movements significantly contributes to the return predictive power that we document throughout the paper. [14]

In summary, we find that foreign investors can process local firm information, especially the most value-relevant information related to large stock price movements. Given the potential information asymmetry induced by geographic distance, foreign institutions may establish offices in places nearby Mainland China, like Hong Kong.[15] They can also hire managers with Chinese ethnicity to overcome culture barriers. For example, Bai et al. (2021) show that the foreign origin of funds managers is an important driver of US mutual funds' abnormal performance linked to their offshore holdings. Overall, our findings provide supportive evidence to the argument presented in Froot and Ramadorai (2008) that foreign investors might possess informational advantages regarding fundamental information in local markets.

14 In Table IA.IX, we separate media news days with large price movements into positive and negative return days, we find QFII and local institutions have higher return predictive power on media news days with negative returns. In the Internet Appendix Table IA.XI, we directly investigate foreign investors' performance on stocks with large daily returns. The results show that foreign investors have stronger return predictive power on these large return days.

[15] Regarding SAFE's list on May 29, 2020, around 25% of QFIIs locate in Hong Kong. The number is 43% for RQFII.

C. Market-Level Information and Return Predictive Power

Besides public firm information, market-level information is also important for asset price determination. Given foreign investors in China are mostly international institutions, we anticipate that foreign investors may be able to process market-level news, especially global news. According to Hypothesis 3a, the predictive power of foreign investors' trade flows should be stronger on market-level news days than on non-news days, especially if it is news related to the global capital market.

The most significant news at the market level is the market return itself, which presumably contains all information happening at the aggregate level. Therefore, we use returns on a value-weighted portfolio of all Chinese A-share stocks as a proxy for local market information, returns on the CRSP value-weighted portfolio of all stocks on the NYSE/AMEX/NASDAQ as a proxy for foreign market information, and returns on the MSCI World Index as a proxy for global market information. Following the previous logic, we assume that unexpected valuable market-level news leads to large price movements for market indices. Then, we examine foreign investors' return predictive power on days with and without large aggregate market price movements. Notice that from equation (2), we obtain the time-series of coefficient $\widehat{a1}(d, G)$ for each day. To understand the dynamics of $\widehat{a1}(d, G)$, we link it to the large market returns as follows:

$$\widehat{a1}(d, G) = b0(G) + b1(G)TailMarket(d) + \epsilon(d, G) \quad (9)$$

Here, the indicator variable $TailMarket(d)$ equals 1 if the stock market return on day d is outside the 5th and 95th percentiles of all market return days in the sample, and otherwise it is zero. This specification is different from equations (7) and (8), which pertain to firm-level news. There, with cross-sectional variation, we directly interact firm news with firm-level order flows. In contrast, for market-level news, there is an absence of cross-sectional variation, so we instead directly examine the time-series properties of the coefficients. Therefore, a positive coefficient $\widehat{b1}(G)$ suggests that investors can access and process market-level information, which affects their predictive power of *Oib* on days with large market returns. Standard errors of the time-series coefficients are adjusted using the Newey-West (1987) methodology, with five lags.

Table VII reports the estimation results for equation (9). In Panel A, we examine how the Chinese market-level news is related to the predictive power of foreign investors' order flows. The $\widehat{b0}$ coefficient is always positive and significant, showing significant predictive power of all order flow measures for next-day returns when there is no large movement in market returns. For the interaction term, the $\widehat{b1}$ coefficient is insignificant for all foreign investors and is significantly negative for local institutions at 95% confidence level. Interestingly, the results suggest that both foreign and local investors, at best, lack predictive power on days with large local market movements.

In terms of U.S and global stock markets in Panel B and C, the patterns are somewhat different. First, the $\widehat{b1}$ coefficient is positive for all investor groups, indicating that they may have higher return predictive power on days when U.S or global market experience large movements. Second, at the 90% confidence level, the $\widehat{b1}$ coefficient is marginally significant for QFII on days with large global market movements. Further, it is significant for HKC on days with large U.S market movement. The interquartile returns for QFII on days with large U.S and global market movement are 0.1458% and 0.1566% separately, the highest among our investor groups.[16]

[16] In Internet Appendix Table IA.X, we find QFII has significantly higher return predictive power on days when U.S or global market experience large negative returns. Local institutions have better performance when local and global stock markets have large negative returns.

Regarding the results, we find some supportive evidence to Hypothesis 3a that foreign investors may be able to process global market information. However, the evidence is relatively weak.[17,18]

When we compare the predictive results on firm-level and market-level news days, it seems that both foreign and local investors possess greater informational advantages regarding firm-specific information than market level news. We believe this is an interesting and important finding of the paper. It is possible that market-level news, especially news events related to strong price reactions, are unpredictable shocks and/or reflect highly confidential policies or macroeconomic data releases, and thus investors cannot gather useful information and make precise predictions prior to announcements. Meanwhile, regarding the strong and significant predictive power of foreign investors' order flow around firm-level news days, it is likely that the maturing information environment in China, together with the experience and diligence of sophisticated foreign investors make up for otherwise potential disadvantages of foreign investors in the local market. This now leads to comparable performance between foreign and local institutions regarding firm-level news days.

[17] To test this further, in Internet Appendix H and Table IA.XII, we use macroeconomic announcements as proxies for market-level news. Following Bernile, Hu and Tang (2016), we collect U.S. macroeconomic announcements including scheduled announcements of the federal funds target rate by the Federal Open Market Committee (FOMC), the release of GDP growth rate by the Bureau of Economic Analysis (BEA), the release of PPI and nonfarm payroll by the Department of Labor and. For comparison, we select Chinese macroeconomic announcements in similar categories, which include announcements of M2 growth by the People's Bank of China (PBoC), the release of GDP growth, PPI, and unemployment rate by National Bureau of Statistics (NBS). We convert U.S Eastern Standard Time to China Standard Time and match all announcements time with the relevant trading day. Our sample covers 153 U.S and 112 China macroeconomic announcements, leading to 147 and 105 unique news-related trading days, respectively. Nearly all results are statistically insignificant. We only find that, at the 90% confidence level, QFII has significantly higher return predictive power on days when there are announcements related to M2 growth and U.S PPI. We do observe that local institutions do somewhat better predict stock returns on days with a China unemployment data release. One implication of these findings is that these macroeconomic announcements are not associated with large Chinese A-share stock returns.

[18] In addition, in Internet Appendix I and Table IA.XIII, we use the Citigroup economic surprise index (CESI) as an additional proxy and do not find a significant relation between investors' return predictive power and large surprises.

D. Stock Market Liberalization

During our sample period, China gradually relaxes the QFII, RQFII and HKC regulations to permit greater access to foreign investors. These reforms clearly facilitate the entrance of foreign investors to Chinese market, which also provide an opportunity for us to examine how foreign investors' return predictive power evolves along with a greater degree of regulatory access.

There are three major policy changes for the QFII program in our sample. First, on February 3, 2016, the State Administration of Foreign Exchange (SAFE) announced to increase the maximum basic investment quota for a single QFII from $1 billion to $5 billion. Second, on June 10, 2018, SAFE announced the removal of the 3-month lock-up period and the maximum 20% capital repatriation limitation for QFII. Third, on January 14, 2019, SAFE announced an increase in QFII's total investment quota from $150 billion to $300 billion. There are two major policy changes for the RQFII program. RQFIIs originally were not allowed to invest in stocks or stock investment funds at levels that exceeded 20% of its raised capital. CSRC verbally announced the lifting of that restriction at a press conference on September 30, 2016. Then, on June 11, 2018, SAFE announced the removal of the 3-month lock-up period for RQFII. Finally, there are two regulatory changes for 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 seven regulation dummy variables, $Quota2016QFII(d)$, $FX2018QFII(d)$, $Quota2019QFII(d)$, $Invest2016RQFII(d)$, $FX2018RQFII(d)$, $Quota2016HKC$ nd $Quota2018HKC$. Each dummy variable is equal to zero before the related event occurs and one afterwards.

To examine the relationship between regulatory reform and foreign investors' return predictive power, we first obtain the time-series of coefficient $\widehat{a1}(d,G)$ for each day, as in equation (2). Then we link the dynamics of $\widehat{a1}(d,G)$ with the regulation dummies, as follows,

$$\widehat{a1}(d,G) = b0(G) + b1(G)'Regulations(d-1) + \epsilon(d,G) \tag{10}$$

According to Hypothesis 4a, if relaxing regulations provides greater access or lower transactions cost for foreign investors in China stock market, we expect that foreign investors' predictive power increases after a particular regulation change, implying positive values of the coefficient vector $\widehat{b1}(G)'$.

Table VIII reports the estimation results. For QFII, we observe a significantly positive coefficient on *Quota2016QFII*, which indicates an increase in return predictive power since February 2016. We do not find a significant relationship between policy changes and RQFII's return predictive power. For HKC, the coefficients on *Quota2016HKC* and *Quota2018HKC* are 0.0234 and 0.0913 with *t*-statistics of 2.05 and 5.25, meaning that HKC better predicts stock returns after the expansion of investment quotas.

Relaxing regulations is not always linked to an increase in the predictive power of foreign investors for local returns. On the one hand, enlarging the investment quota reduces investment constraints and attracts informed investors entering the market, as in Hypothesis 4a. On the other hand, local stock markets become accessible to less-informed investors, as in Hypothesis 4b. Our results imply that to some extent, the relaxation of investment access can improve foreign investors' return predictive power, suggesting that more informed trading is reflected in foreign capital flows in aggregate after the relaxation of regulations, which supports the Hypothesis 4a.

V. Further Discussion

A. Price Pressure

Ferreira et al. (2017) find that foreign investors' predictive power is better characterized by a price pressure explanation rather than as a reflection of underlying fundamentals. Here we decompose the order flow measures into two components, a 20-day moving average measure, $MAOib$, to capture a persistent component of the order imbalance variable, and the difference between the Oib and the $MAOib$, $ShockOib$, designed to capture the day-to-day fluctuations in order flows. We then examine whether foreign investors' return predictive power is driven by the moving average component or the daily change component.

Panel A of Table IX reports the estimation results. For both foreign investors and local institutions, the coefficients of $MAOib$ and $ShockOib$ are both positive and statistically different from zero, indicating that both persistent and temporary order flows contribute to investors' predictive power. To determine the relative importance of these two components, we separately calculate interquartile returns for the two measures. The contribution of $MAOib$ to investors' performance is defined as the related interquartile return divided by the sum of interquartile returns of $MAOib$ and $ShockOib$. Take QFII as an example. The interquartile returns for $MAOib$ and $ShockOib$ are 0.0382% and 0.0924%, separately. The contribution of $MAOib$ to overall performance is 0.0382%/(0.0382%+0.0924%)=29.26%, less than the contribution of $ShockOib$. We observe similar patterns for the other three investor groups. The results reveal that though persistent trading partly explains investors' performance, a larger portion of investors' return predictive power is nevertheless attributed to the $ShockOib$, meaning that price pressure is not the main source of investors' return predictability.

B. Dual-listed Firms

Fernandes and Ferreira (2008) suggest that cross-listing may increase analyst coverage and public information but reduce the active trading of informed traders. We then examine whether foreign investors' predictive power differs between cross-listed firms that have H shares listed on the Hong Kong Stock Exchange and other firms. We estimate the following Fama-MacBeth regression:

$$Ret(i,d) = a0(d,G) + [a1(d,G) + a2(d,G)Duallist(i,d-1)] \times Oib(i,d-1,G)$$
$$+a3(d,G)Duallist(i,d-1) + a4(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \qquad (11)$$

where the dummy variable $Duallist(i,d-1)$ equals 1 if stock i on day $d-1$ has a dual-listed H share; otherwise, it equals 0.

The estimation results are presented in Table IX Panel B. If we only consider foreign investors' order flows, there are no significant differences in their predictive powers for firms with and without dual listings. Interestingly, the predictive power is significantly higher when we examine local institutions' order flows to predict stock returns, suggesting that local institutions are better informed regarding firms with dual listings.

C. State-Owned Enterprises (SOEs)

As a developing economy, the Chinese government exerts significant influence on state-owned enterprises. SOEs are generally criticized for their less transparent information environment, poor financial performance, and potential agency problems. Leippold, Wang and Zhou (2021) find that the return predictability on SOEs is weaker than that of non-SOEs over a monthly horizon. Would that affect the predictive patterns of foreign order flows? To answer this question, we replace the dummy variable $Duallist(i,d-1)$ in equation (11) by an SOE dummy,

$SOE(i, d-1)$, which equals 1 for stocks whose controlling shareholders are state-owned enterprises, and otherwise zero.

We report the estimation results in Panel C of Table IX. Across all investor groups, there coefficients on the interaction of *Oib* and SOE dummy are generally statistically insignificant, indicating that the informativeness of these investors is not affected by a firms' state ownership.

D. Index Constituents

Passive investors tend to trade indices directly rather than individual stocks, which potentially creates differences in the information environment for index constituent firms vs. non-constituent firms. We consider two influential indices, the local Chinese Stock Index 300, or the CSI300, which tracks the performance of the top 300 A-share stocks and is widely used by local investors, and the MSCI Emerging Market Index, which include large-cap A-shares that are eligible for HKC investors and is the benchmark for many international funds. As before, we replace the dummy variable $Duallist(i, d-1)$ in equation (11) by constituent dummies, $CSI(i, d-1)$ and $MSCI(i, d-1)$, which equal 1 for stocks belonging to each index, and zero otherwise.

For the CSI 300 and MSCI results in Panel D and E of Table IX, we find index inclusions do not affect the predictive power of foreign investors' order flows. However, the predictive power of local institutions is interestingly and significantly higher for firms in the CSI 300 and MSCI, implying that local institutions are better informed about these index constituent firms.

E. Firms with Cross-Border Business Activities

Chinese firms are important participants in the global supply chain both as suppliers and, increasingly, consumers. Our evidence on foreign investors' strong predictive power on firm level news days may be linked to the fact that foreign investors are more familiar with local firms that have cross-border business activities or the firm-level news on which we focus is increasingly driven by exeternal, global factors. To examine this possibility, we investigate whether foreign investors' predictive power is related to firm level overseas activities. In China, public-listed firms disclose overseas revenue in semiannual and annual financial statements. Here, we use the absolute value of the ratio of overseas revenue to total revenue, $|Overseas(i, d-1)|$, as a measure of firms' cross-border business activities. To be more specific, we replace the dummy variable $Duallist(i, d-1)$ in equation (11) by, $|Overseas(i, d-1)|$.

Panel F in Table IX presents the estimation results. For foreign investors and local institutions, the return prediction coefficients on the interaction between investor order imbalance and a firm's overseas revenue are all positive, ranging between 0.0427 and 0.0720. Except for RQFII, these coefficients are significantly different from zero, suggesting that the predictive power of order flows are stronger for firms with more overseas activities. While this may suggest foreign investors are more familiar with these firms or they better understand a global component of their performance, these results are interestingly also true for local institutional investors. In terms of economic magnitudes, the interquartile return for QFII on hypothetical firms with unit overseas ratio is 0.1925% per day, higher than 0.1327% for local institutions, indicating that foreign investors may possess informational advantages on firms with significant cross-border business.

F. Eligible Stocks in HKC Program

The results we report so far are based on the entire A-share universe, given that QFIIs and RQFIIs can invest in any A-share stocks. The restriction is different for HKC investors, who can only invest in constituent stocks of the SSE 180 Index and SSE 380 Index and A shares that have H shares listed in Hong Kong Stock Exchange. Therefore, this section restricts our sample to the eligible stocks that HKC can invest in and examines whether our original results are robust, using the Fama-MacBeth regression in equations (2) and (3).

Panel G in Table IX presents the next-day's return prediction results. Even for this smaller group of stocks, the coefficients on *Oib* are again positive and significant at the 99% confidence level for all investor groups. The interquartile returns are 0.1125%, 0.0430%, 0.0853% and 0.1087%, close to those in Panel A Table III. Panel H presents longer-horizon cumulative return prediction results. In this subsample, we continue to find that foreign investors significantly predict stock returns over longer periods. [19]

VI. Conclusions

We investigate whether foreign investors are informed in the Chinese stock market using a comprehensive account-level dataset covering January 1, 2016 to June 30, 2019. We find that QFII, RQFII, and HKC investors can predict future stock price movements over both short and longer horizons. When relating their predictive power to firm-level information, we find that foreign investors can successfully process firm-specific information. Their return predictive power is significantly stronger on the most value-relevant firm news days with large price movements, and the magnitude is comparable among foreign and local institutions. We find similar evidence using local and global market-level information, but the magnitude is smaller, and the significance is lower. The evidence suggests that the foreign investors are not at an informational disadvantage for firm-level information to local institutions, contrary to most previous studies. Finally, during the market liberalization process, we find that expanding investment quotas helps to improve foreign investors' return predictability.

These findings have important implications for policymakers and researchers. Regulators should promote the development of price discovery and financial market efficiency by further

[19] The Chinese A-share stock market imposes 10% limits on daily stock prices (5% for special treatment stocks). In unreported results, we remove observations (representing 1.71% of the total sample) where stocks hit the daily price limits as this may cloud inference. The return predictive patterns still hold.

examining how to take advantage of foreign investors' abilities. Identifying how foreign investors trade during the COVID-19 period, relative to their local counterparts, also presents a promising avenue for future research.

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Table I
Institutional background of QFII, RQFII and HKC in China

This table summarizes the differences in QFII, RQFII and HKC investors in China.

	QFII	RQFII	HKC
Investor	1.Institutional investors such as security companies, commercial bank, asset management company and others 2. Requirements on the scale of asset under management and operation periods.	1.In 2011, only Hong Kong subsidiaries of Chinese financial institution 2.gradually extended to other locations.	Hong Kong and oversea investors, including both retail and institutional investors.
Investable Stock	1. All A-share stocks listed in exchanges 2. Fixed income and other financial products	1. All A-share stocks listed in exchanges 2. Fixed income and other financial products	1.Constituent stocks of the SSE 180 Index and SSE 380 Index. 2.A shares with H shares listed in HK
Investment Quota	1. Basic quota for a single QFII was limited by the scale of asset under management and was no more than $5 billion 2. Aggregated 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 asset under management 2. Aggregated RQFII quota varies for different locations. For example, the aggregated 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.
Ownership	1. A single QFII licensee or RQFII license 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 can't exceed 30% of its total outstanding shares.		
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
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 the total asset 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

Table II
Summary statistics of foreign investors and local institutions

This table summarizes trading and holdings by foreign investors and local institutions. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of the Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. Foreign investors refer to as Qualified Foreign Institutional Investors (QFII), Renminbi Qualified Foreign Institutional Investor (RQFII) and investors via Shanghai-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, 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 cross-sectional mean, standard deviation, median, 25th and 75th percentiles of our order imbalance variable. *AR(1)* is the cross-sectional mean of first-order autocorrelation of the order imbalance measure. Panel C reports the time-series average of cross-correlations of the order imbalance measure across investor groups.

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

	QFII	RQFII	HKC	Local INST
Number of stocks held	1,261	901	744	1,297
Number of stocks traded	946	174	561	1,227
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%
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%

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

	Mean	Std	P25	P50	P75	AR(1)
Oib(QFII)	-0.01	0.86	-0.92	-0.02	0.91	0.09
Oib(RQFII)	0.02	0.82	-0.61	0.07	0.62	0.44
Oib(HKC)	0.02	0.58	-0.46	0.04	0.51	0.12
Oib(Local INST)	-0.01	0.47	-0.36	-0.01	0.34	0.18

Panel C. Correlations of the order imbalance measure across investor groups

	Oib(QFII)	Oib(RQFII)	Oib(HKC)	Oib(Local INST)
Oib(QFII)	1			
Oib(RQFII)	0.09	1		
Oib(HKC)	0.14	0.04	1	
Oib(Local INST)	0.09	0.06	0.06	1

Table III

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 in both short-term and long-term horizons. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate daily Fama-MacBeth (1973) regressions. Panel A presents results on the next day's return prediction, as in equation (2). Panel B presents the coefficients on the order imbalance measure in the w weeks cumulative return prediction, as in equation (3). 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 also control the log of market capitalization *(Lnsize)*, earnings-to-price ratio *(EP)* and monthly turnover *(Turnover)*, all measured at the end of previous month. *Adj-R^2* is the time-series average of adjusted R-squared in the cross-sectional regression. *Interquartile* is the time-series average of the cross-sectional interquartile range of the order imbalance variable. *Interquartile Return* represents the magnitude of investor's return predictability, defined as *Interquartile* multiplied by the estimated coefficient on the order imbalance. To account for potential serial correlation in the coefficients, the standard errors are adjusted using Newey-West (1987) with five lags. We report *t*-statistics in the 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***
	(17.02)	(3.10)	(10.44)	(18.57)
Ret(d-1)	0.7388	-0.3870	0.2152	2.2033***
	(1.54)	(-0.61)	(0.37)	(4.32)
Ret(d-6, d-2)	-0.8924***	-0.5660**	-0.7376***	-1.1077***
	(-4.48)	(-2.06)	(-3.20)	(-5.88)
Ret(d-27, d-7)	-0.2353***	0.0237	-0.2095**	-0.3077***
	(-2.75)	(0.17)	(-2.03)	(-4.68)
Lnsize	-0.0078	0.0034	0.0045	-0.0016
	(-0.78)	(0.32)	(0.44)	(-0.16)
EP	1.3757***	1.2805	1.5416***	1.4607***
	(2.91)	(1.62)	(2.82)	(3.22)
Turnover	-0.0521***	-0.1848***	-0.1121***	-0.0556***
	(-2.66)	(-3.49)	(-4.35)	(-3.25)
Adj-R^2	8.96%	14.75%	10.07%	8.83%
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%***	-0.1221%***	0.1144%***	-0.1436%***	0.2546%***
3	0.2789%***	-0.0128%	0.1704%***	-0.0815%**	0.1228%***	-0.1725%***	0.2916%***
4	0.3088%***	-0.0129%	0.1844%***	-0.1331%**	0.1293%***	-0.1917%***	0.3217%***
5	0.3255%***	-0.0127%	0.2578%***	-0.1325%	0.1303%***	-0.2091%***	0.3381%***
6	0.3356%***	-0.0325%	0.2549%***	-0.1102%	0.1541%***	-0.2141%***	0.3681%***
7	0.3784%***	-0.0191%	0.2662%***	-0.0527%	0.1796%***	-0.2185%***	0.3975%***
8	0.3973%***	-0.0261%	0.3004%***	-0.0576%	0.1811%***	-0.2431%***	0.4234%***
9	0.3877%***	-0.0337%	0.2908%***	-0.1060%	0.1544%***	-0.2701%***	0.4214%***
10	0.4178%***	-0.0199%	0.3289%***	-0.1221%	0.1644%***	-0.2734%***	0.4377%***
11	0.4367%***	-0.0103%	0.3956%***	-0.0815%	0.1667%**	-0.2797%***	0.4470%***
12	0.4586%***	0.0021%	0.3999%***	-0.1331%	0.1621%**	-0.2941%***	0.4565%***

Table IV

Stock return predictive power of overlapping and specific order imbalances

This table reports estimation results on the predictive power of overlapping and specific order imbalances by foreign investors and local institutions. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of the Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate Fama-MacBeth regressions, as in equation (6). *Oib(overlapping with local)* and *Oib(foreign specific)* are overlapping and specific order flows for foreign investors defined in equation (5). A similar procedure is used to decompose local institutions' order imbalance measure into *Oib(overlapping with foreign)* and *Oib(local specific)*. *Interquartile* is the time-series average of cross-sectional interquartile ranges of investors' overlapping and specific trading. Control variables are the same as those in equation (2). To spare the space, we omit the coefficients of control variables. *Interquartile return* is defined as *Interquartile* multiplied by the estimated coefficient on the related order imbalance. *Adj-R^2* is the time-series average of adjusted R-squared in the cross-sectional regression. 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 the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1, overlapping)	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, overlapping)				0.7173***
				(4.50)
Oib(d-1, local specific)				0.2355***
				(11.03)
Adj-R^2	9.18%	15.07%	10.32%	16.39%
Interquartile Return				
Oib(d-1, overlapping with local)	0.0399%	0.4916%	0.1330%	
Oib(d-1, foreign specific)	0.1034%	0.0240%	0.0670%	
Oib(d-1, overlapping with foreign)				0.0769%
Oib(d-1, local specific)				0.1205%

Table V

Stock return predictive power, earnings, and analyst-related events

This table presents the estimation results on whether the return predictive power of foreign investors and local institutions is related to firm earnings announcements and analyst-related events. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. Our sample covers 15,477 earnings announcements and 41,722 analyst-related events, totaling 50,331 event days. We estimate quarterly Fama-MacBeth regressions as in equation (7). In each calendar quarter, we perform OLS regression and calculate the time-series average of coefficients. Indicator variable *Tail(i, d)*=1 if stock *i*'s return on event day *d* is outside the 5^{th} and 95^{th} percentiles of all event day returns, and otherwise it is zero. *NTail(i, d)*=1 if stock *i*'s return on event day *d* is inside the 5^{th} and 95^{th} percentiles of event day returns and otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and *t*-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0977***	0.0433***	0.0954***	0.2120***
$\widehat{a2}$: Oib(d-1)×Tail (d)	0.5177***	0.6788***	0.3035	2.4531***
$\widehat{a3}$: Oib(d-1)×NTail (d)	-0.0342***	0.0292	0.0824**	-0.0042
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$(Non-event)	0.1787%	0.0535%	0.0922%	0.1487%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(Tail)	1.1259%	0.8913%	0.3856%	1.8688%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a3})$:$\widehat{Ret}3$(Non-tail)	0.1161%	0.0896%	0.1718%	0.1457%
$\widehat{Ret}2$ on tail event days as a percentage of overall performance (0.49%)	3.06%	7.38%	1.94%	5.83%
$\widehat{Ret}3$ on non-tail event days as a percentage of overall performance (4.45%)	2.86%	6.73%	7.87%	4.13%

Table VI

Stock return predictive power and media news

This table presents the estimation results on whether return predictive power of foreign investors and local institutions is related to local media news. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We obtain news information from CNRDS. Our sample includes 353,551 news days accounting for 34.69% of all observations. We estimate quarterly Fama-MacBeth regressions, as in equation (8). *TailNews(i, d)*=1 if stock *i*'s return on news day *d* is outside the 5^{th} and 95^{th} percentiles of all news day returns and otherwise it is zero. *NTailNews(i, d)*=1 if stock *i*'s return on news day *d* is inside the 5^{th} and 95^{th} percentiles of all news day returns and otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and *t*-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1)	(2)	(3)	(4)
	QFII	RQFII	HKC	Local INST
$\widehat{a1}$: Oib(d-1)	0.0906***	0.0323*	0.0910***	0.1847***
$\widehat{a2}$: Oib(d-1)×TailNews (d)	0.3550***	0.2713	0.1473	1.4984***
$\widehat{a3}$: Oib(d-1)×NTailNews (d)	-0.0085	0.0162	0.0156	-0.0553*
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$(Non-news)	0.1657%	0.0398%	0.0880%	0.1295%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(Tail news)	0.8153%	0.3747%	0.2304%	1.1802%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a3})$: $\widehat{Ret}3$(Non-tail news)	0.1502%	0.0599%	0.1031%	0.0908%
$\widehat{Ret}2$ on tail news days as a percentage of overall performance (3.47%)	15.42%	22.53%	8.18%	26.61%
$\widehat{Ret}3$ on non-tail news days as a percentage of overall performance (31.23%)	25.57%	32.39%	32.97%	18.42%

Table VII
Stock return predictive power and market movement

This table presents estimation results on whether the return predictive power of foreign investors and local institutions is related to stock market movements. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of the Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We use a value-weighted portfolio of all A-share stocks as a proxy for the Chinese stock market, the CRSP value-weighted portfolio of all stocks on the NYSE/AMEX/NASDAQ as a proxy for the US stock market, and the MSCI World Index as a proxy for the global stock market. The indicator variable *TailMarket(d)*=1 if on day *d* the market return is outside the 5^{th} and 95^{th} percentiles of whole sample returns, otherwise zero. As shown in equation (9), we apply a two-step regression procedure. In the first step, we perform OLS regression on each day and obtain the time-series coefficients of *Oib(d-1)*, $\widehat{a1}(d)$. In the second step, we regress the estimated coefficient on the market indicator variable. Panel A, B and C present the second-step regression results with the Chinese stock market proxy, the US stock market proxy and the global stock market proxy, respectively. The standard errors are adjusted using Newey-West (1987) with five lags. To spare the space, we omit *t*-statistics in the table. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. The Chinese stock market

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0673***	0.0276***	0.0754***	0.1378***
$\widehat{b1}$: TailMarket (d)	-0.0241	0.0173	0.0285	-0.0487**
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$(Non-tail market return)	0.1231%	0.0341%	0.0729%	0.0966%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Tail market return)	0.0790%	0.0554%	0.1004%	0.0625%
$\widehat{Ret}2$ on tail market return days as a percentage of overall performance (9.89%)	6.58%	15.15%	13.13%	6.63%

Panel B. The US stock market

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0624***	0.0255***	0.0724***	0.1310***
$\widehat{b1}$: TailMarket (d)	0.0173	0.0452	0.0612*	0.0341
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$(Non-tail market return)	0.1142%	0.0315%	0.0700%	0.0919%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Tail market return)	0.1458%	0.0873%	0.1291%	0.1158%
$\widehat{Ret}2$ on tail market return days as a percentage of overall performance (9.98%)	12.40%	23.50%	16.98%	12.26%

Panel C. The global stock market

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0627***	0.0247***	0.0750***	0.1300***
$\widehat{b1}$: TailMarket (d)	0.0229*	0.0450	0.0376	0.0316
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$(Non-tail market return)	0.1147%	0.0304%	0.0725%	0.0911%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Tail market return)	0.1566%	0.0860%	0.1088%	0.1133%
$\widehat{Ret}2$ on tail market return days as a percentage of overall performance (9.89%)	13.03%	23.66%	14.15%	12.00%

Table VIII

Stock return predictive power and market liberalization

This table presents estimation results on how foreign investors' return predictive power changes after the relaxation on regulations. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of the Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We apply a two-step regression procedure, as in equation (10). In the first step, we perform OLS regression on each day and obtain the time-series coefficients of *Oib(d-1)*, $\widehat{a1}(d)$. In the second step, we regress the estimated coefficient on a series of indicator variables related to regulations. There are three major policy changes for QFII. First, on February 3, 2016, the State Administration of Foreign Exchange (SAFE) announced to increase in the maximum basic investment quota for a single QFII from $1 billion to $5 billion. Second, on June 10, 2018, SAFE announced the removal of the 3-month lock-up period and the maximum 20% capital repatriation limitation for QFII. Third, on January 14, 2019, SAFE announced an increase in QFII's total investment quota from $150 billion to $300 billion. There are two major policy changes for the RQFII program. RQFII originally were not allowed to invest in stocks or stock investment funds at levels that exceeded 20% of its raised capital. CSRC verbally announced the lifting of that restriction at a press conference on September 30, 2016. Then, on June 11, 2018, SAFE announced the removal of the 3-month lock-up period for RQFII. Finally, 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 seven regulation dummy variables, *Quota2016QFII, FX2018QFII, Quota2019QFII, Invest2016RQFII, FX2018RQFII, Quota2016HKC* and *Quota2018HKC*. Each dummy variable is equal to zero before the related event occurs and one afterward. Panel A, B and C show the results on the second step regressions for QFII, RQFII and HKC respectively. *Adj-*R^2 is the adjusted R-squared in the second step regression. To account for serial correlation in the coefficients, the standard errors are adjusted using Newey-West (1987) with five lags. We report *t*-statistics in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Regulation changes on QFII

Dep: $\widehat{a1}(d)$	(1) QFII
Intercept	0.0095
	(0.61)
Quota2016QFII(d-1)	0.0585***
	(3.66)
FX2018QFII(d-1)	0.0028
	(0.27)
Quota2019QFII(d-1)	-0.0187
	(-1.18)
Adj-R^2	0.59%

Panel B. Regulation changes on RQFII

Dep: $\widehat{a1}(d)$	(1) RQFII
Intercept	0.0260*
	(1.81)
Invest2016RQFII(d-1)	-0.0099
	(-0.54)
FX2018RQFII(d-1)	0.0215
	(1.09)
Adj-R^2	-0.09%

Panel C. Regulations changes on HKC

Dep: $\widehat{a1}(d)$	(1) HKC
Intercept	0.0289***
	(3.43)
Quota2016HKC(d-1)	0.0234**
	(2.05)
Quota2018HKC(d-1)	0.0913***
	(5.25)
Adj-R^2	6.58%

Table IX

Stock return predictive power, price pressure, dual-listed stocks, SOEs, index constituents, stocks with cross-border business and subsample test

This table presents the estimation results on how foreign investors' return predictive power is related to price pressure, dual-listed stocks, State-Owned Enterprises (SOEs), index constituents and eligible stocks in HKC program. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. In Panel A, we decompose the order flow measures into two parts, a 20-day moving average measure, *MAOib*, to capture the persistent component of the order imbalance variable, and the difference between the *Oib* and the *MAOib*, *ShockOib,* to capture the day to day fluctuations in order flows. We investigate the return predictive power of *MAOib* and *ShockOib* with daily Fama-MacBeth regressions. In Panel B, we investigate the relation between foreign investors' return predictive power and dual-listed firms with Fama-MacBeth regression specified in equation (11). The dummy variable *Duallist(i, d-1)* is equal to 1 if stock *i* on day *d-1* has a dual-listed H share, otherwise it equals 0. In Panel C, we examine whether foreign investors have different predictive power between SOEs and non-SOEs. We replace *Dualist(i, d-1)* with an SOE dummy, *SOE(i, d-1)*, which equals 1 if the controlling shareholders for stock *i* are state-owned enterprises, and otherwise zero. In Panel D and Panel E, we investigate foreign investors' return predictive power on index constituents stocks. The indicator variable *CSI(i, d-1)* is equal to 1 if stock *i* on day *d-1* is included in the CSI 300 Index, and zero otherwise. *MSCI(i, d-1)* is equal to 1 if stock on day *d-1* is announced to be included in the MSCI Emerging Market Index and zero otherwise. In Panel F, we investigate foreign investors' return predictive power on stocks with cross-border business activities. |*Overseas(i, d-1)*| is the absolute value of the ratio of overseas revenue to total revenue, and it is equal to zero if there is no overseas revenue. Panel G and Panel H present results on the next day's return prediction and *w* weeks cumulative return prediction in a subsample with only eligible stocks in HKC program, as specified in equation (2) and (3) respectively. To spare the space, we omit coefficients of control variables. *Adj-R*^{2} is the time-series average of adjusted R-squared in the cross-sectional regression. 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 the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. moving average vs. shock component of order flows

Dep: Ret(d)	(1)	(2)	(3)	(4)
	QFII	RQFII	HKC	Local INST
MAOib(d-1)	0.1170***	0.0375**	0.0869***	0.3079***
	(9.54)	(2.26)	(5.50)	(12.43)
ShockOib(d-1)	0.0601***	0.0215**	0.0797***	0.1136***
	(15.80)	(2.49)	(9.13)	(16.19)
Adj-R^2	9.01%	14.98%	10.13%	8.93%
Interquartile Return of MAOib	0.0382%***	0.0225%**	0.0179%***	0.0603%***
Interquartile Return of ShockOib	0.0924%***	0.0222%**	0.0669%***	0.0732%***

Panel B. AH dual-listed stocks

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0655***	0.0283***	0.0793***	0.1294***
	(16.86)	(3.14)	(10.25)	(17.87)
Oib(d-1)×Duallist(d-1)	-0.0099	0.0078	-0.0199	0.0712***
	(-1.02)	(0.36)	(-1.27)	(3.46)
Adj-R^2	9.01%	14.82%	10.19%	8.90%

Panel C. SOEs

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0683***	0.0203*	0.0879***	0.1371***
	(13.07)	(1.69)	(9.06)	(15.45)
Oib(d-1)×SOE(d-1)	-0.0071	0.0080	-0.0204*	-0.0100
	(-1.16)	(0.56)	(-1.81)	(-1.00)
Adj-R^2	9.30%	15.11%	10.43%	9.14%

Panel D. Stocks as constituents of CSI300 Index

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0677***	0.0364**	0.0781***	0.1267***
	(16.24)	(2.40)	(10.29)	(17.51)
Oib(d-1)×CSI(d-1)	-0.0064	-0.0147	0.0012	0.0644***
	(-0.77)	(-0.78)	(0.10)	(4.15)
Adj-R^2	9.10%	15.33%	10.23%	8.96%

Panel E. Stocks as constituents of MSCI Emerging Market Index

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0637***	0.0404	0.1414***	0.1853 ***
	(8.31)	(1.24)	(8.84)	(12.94)
Oib(d-1)×MSCI(d-1)	0.0001	0.0015	0.0181	0.0975***
	(0.01)	(0.04)	(0.50)	(2.53)
Adj-R^2	7.63%	15.14%	9.39%	7.67%

Panel F. Stocks with cross-border business activities

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0625***	0.0225**	0.0741***	0.1292***
	(15.48)	(2.55)	(9.44)	(17.63)
Oib(d-1)×|Overseas(d-1)|	0.0427**	0.0524	0.0720**	0.0601**
	(2.33)	(0.48)	(2.04)	(2.01)
Interquartile Returns				
Interquartile Oib(d-1)× $\widehat{a0}$	0.1144%	0.0278%	0.0716%	0.0906%
Interquartile Oib(d-1)× $(\widehat{a0}+\widehat{a1})$	0.1925%	0.0925%	0.1412%	0.1327%

Panel G. One day return prediction with eligible stocks in HKC program

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0627***	0.0367***	0.0904***	0.1754***
	(13.46)	(4.34)	(10.47)	(16.06)
Interquartile	1.7954	1.1716	0.9437	0.6195
Interquartile Return	0.1125%***	0.0430%***	0.0853%***	0.1087%***

Panel H. 12-week cumulative return prediction with eligible stocks in HKC program

Interquartile Cumulative Return Week number w	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
1	0.1620%***	0.0866%***	0.1079%***	0.1923%***
2	0.1741%***	0.1158%***	0.1393%***	0.2670%***
3	0.2179%***	0.1511%***	0.1523%***	0.3125%***
4	0.2496%***	0.1647%***	0.1559%***	0.3763%***
5	0.2540%***	0.1891%***	0.1593%***	0.3967%***
6	0.2786%***	0.1646%**	0.1906%***	0.4418%***
7	0.3170%***	0.1750%**	0.2276%***	0.4775%***
8	0.3409%***	0.1947%**	0.2343%***	0.5056%***
9	0.3274%***	0.1829%**	0.2166%***	0.5037%***
10	0.3667%***	0.2376%***	0.2395%***	0.5354%***
11	0.3623%***	0.3140%***	0.2447%***	0.5419%***
12	0.3713%***	0.3490%***	0.2511%***	0.5528%***

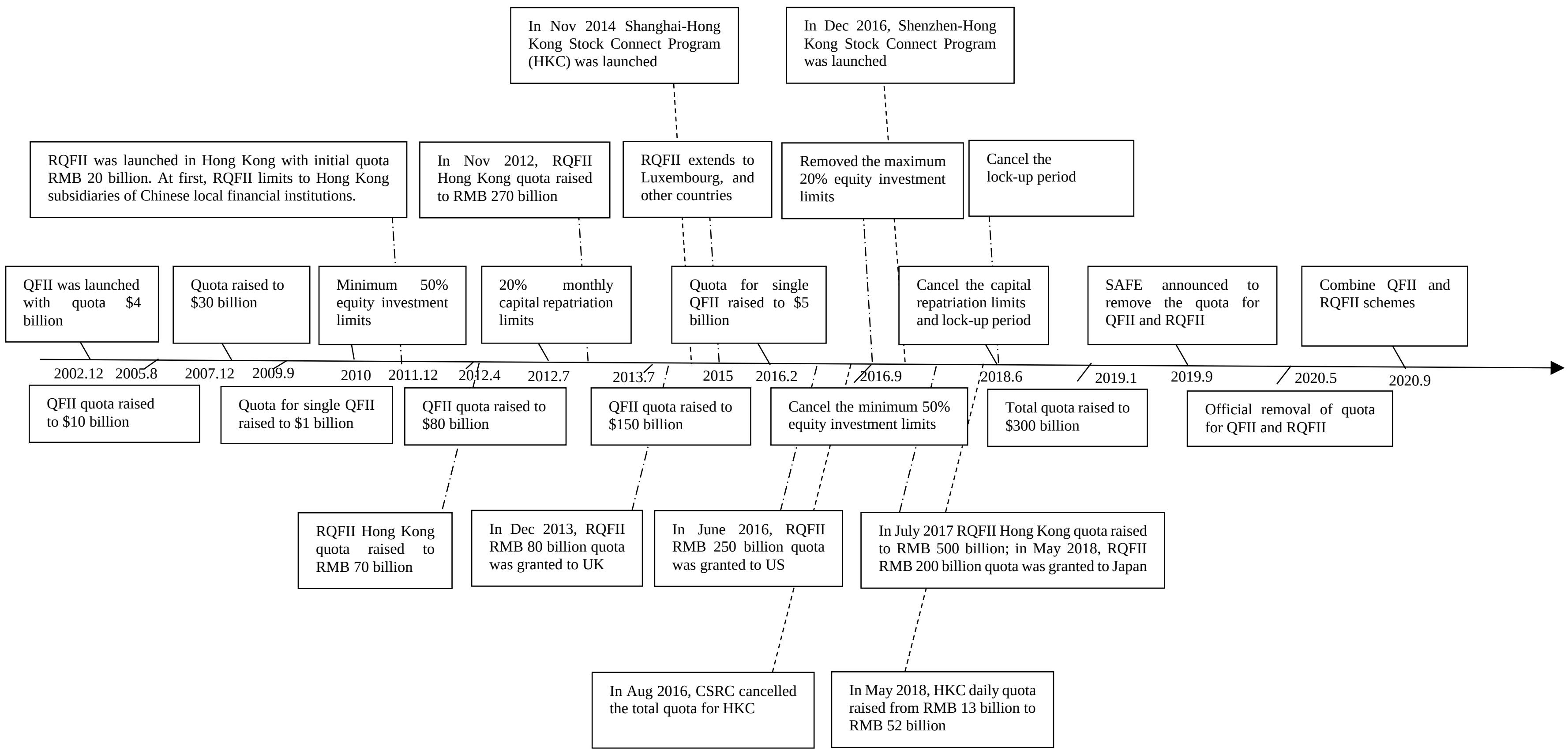
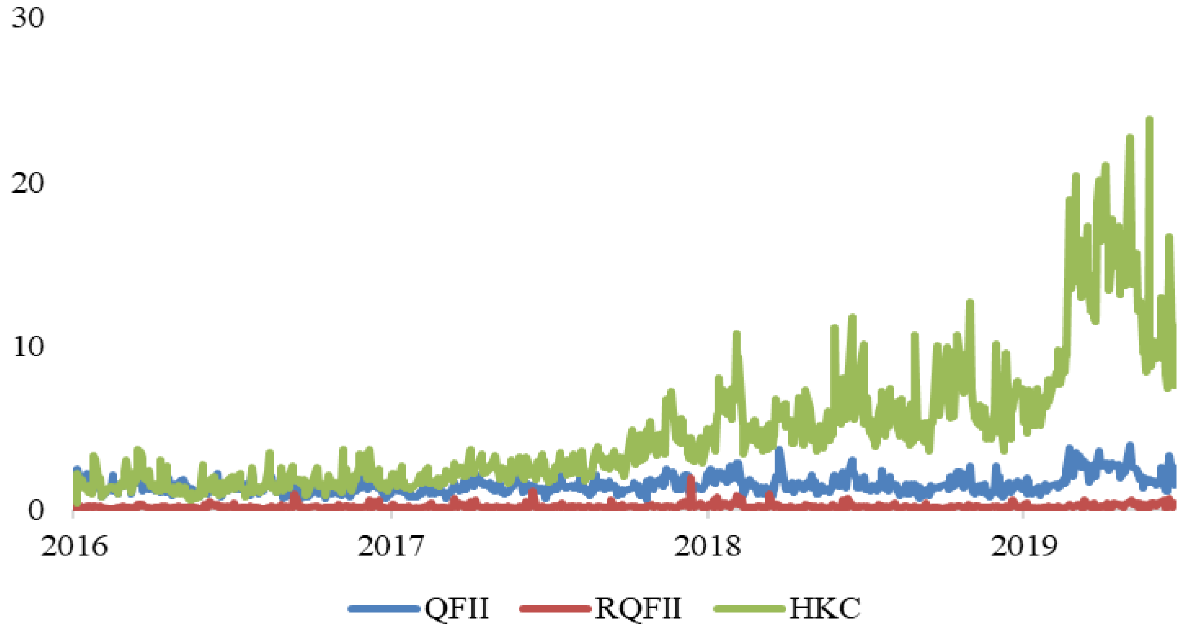


Figure 1. The timeline of QFII, RQFII and HKC in China. This figure presents the key events during the development of QFII, RQFII and HKC in the Chinese stock market.

Panel A. Aggregate trading volume in billion RMB



Panel B. Aggregate holding in billion RMB

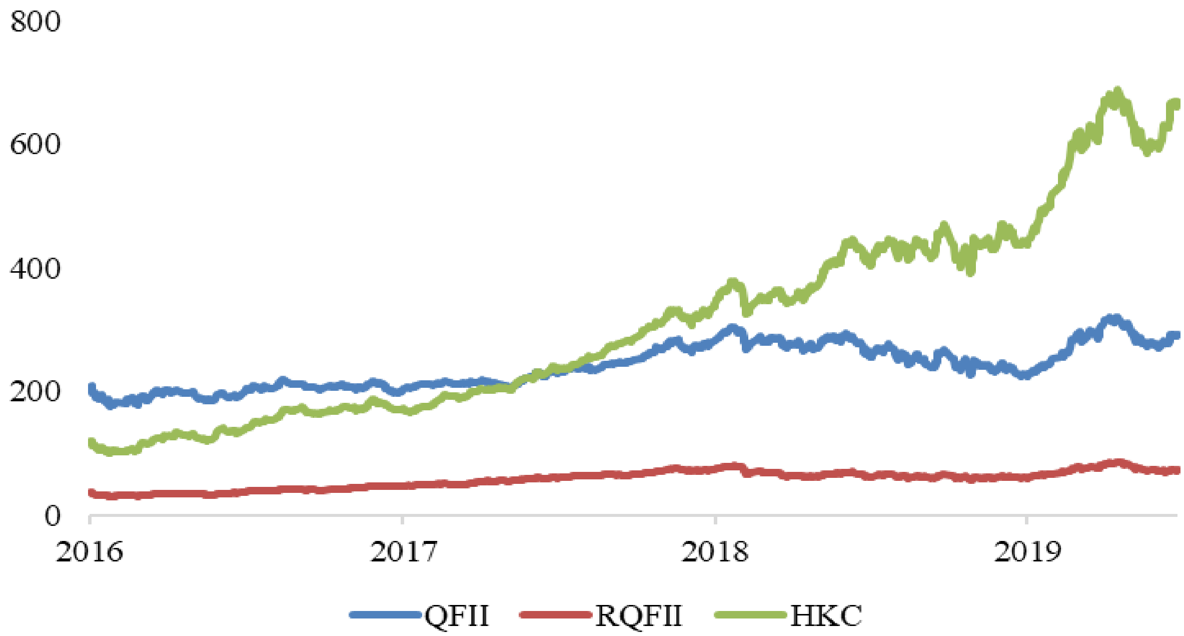


Figure 2. Aggregate trading and holding for QFII, RQFII and HKC. The figure shows the time-series aggregate trading volume and holdings by QFII, RQFII and HKC from January 1, 2016 to June 30, 2019. Panel A shows the time-series aggregate trading volume in billion RMB. Panel B shows the time-series aggregate holdings in billion RMB

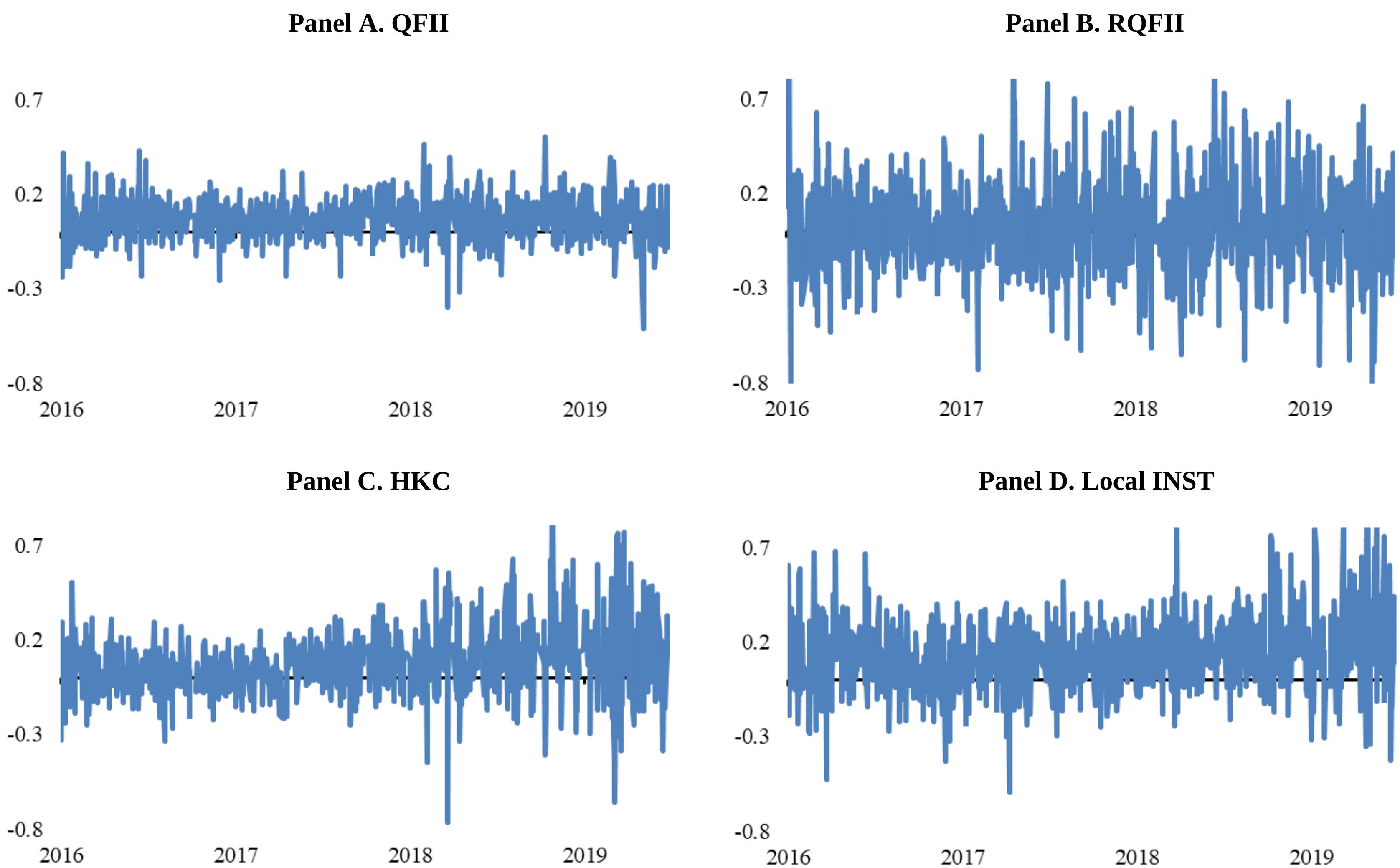


Figure 3. The time-series coefficients of the order imbalance in the next day's return prediction. In equation (2), we use the Fama-MacBeth regression to examine investors' predictive power on the next day's stock return. We plot the time-series coefficients on the previous day's order imbalance in the first-stage regression.

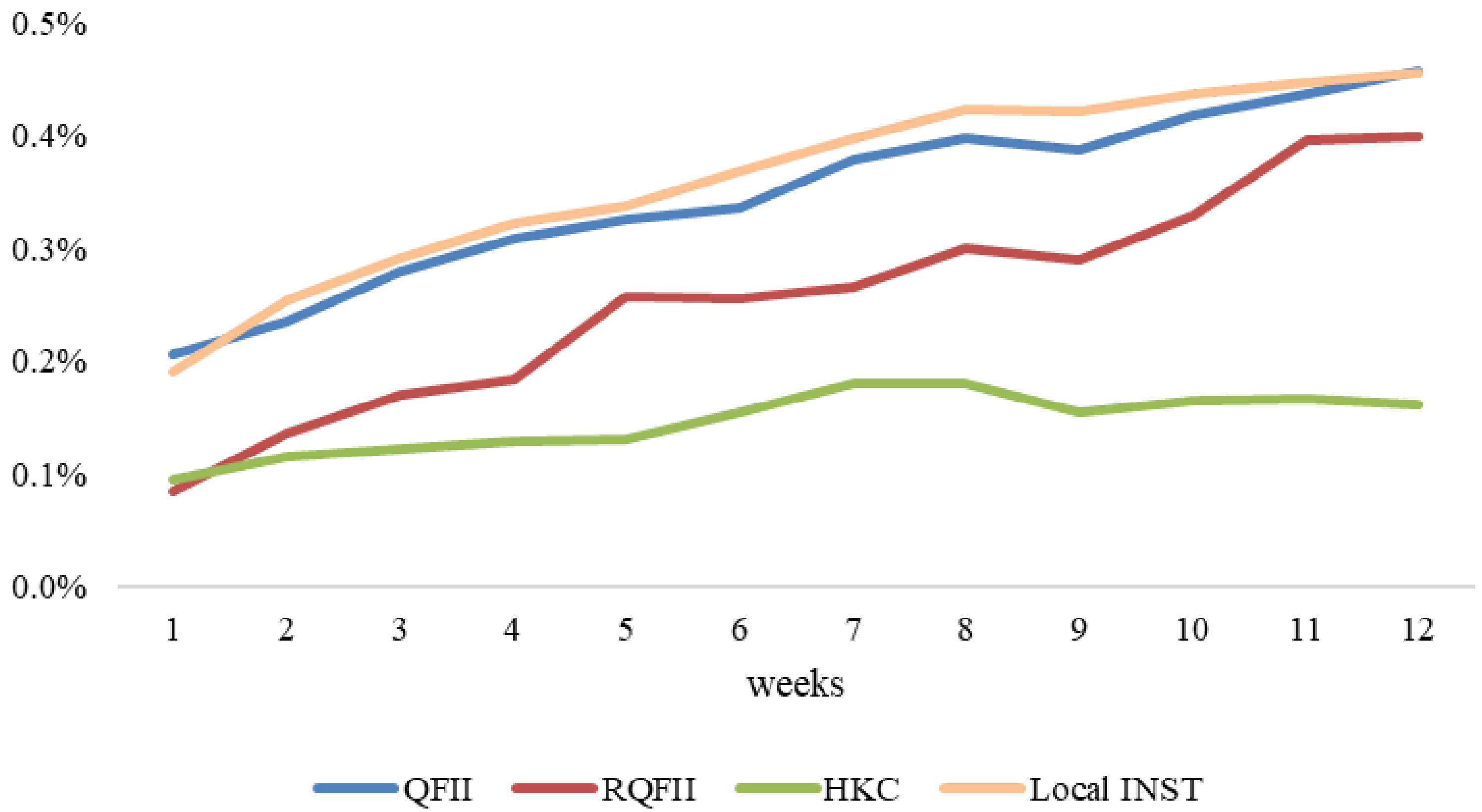


Figure 4. Investors' return predictive power in longer horizons. In this figure, we present the cumulative interquartile returns for different investors over the future 12 weeks, which are calculated as the interquartile of order imbalance multiplied by the coefficients of order imbalance in Table III Panel B.

Internet Appendix for:

"Are Foreign Investors Informed? Trading Experiences of Foreign Investors in China"

A. *Determinants of Investors' Order Imbalances*

We first investigate the determinants of investors' trading flows. We estimate Fama-MacBeth regressions as specified in equation (IA1):

$$Oib(i,d,G) = a0(d,G) + a1(d,G)Ret(i,d-1) + a2(d,G)'Controls(i,d-1) \\ +\varepsilon(i,d,G) \tag{IA1}$$

where the dependent variable $Oib(i,d,G)$ is investor group G's scaled order imbalance measure for stock i on day d. For independent variables, $Ret(d-1)$ is the previous day's stock return. $Ret(d-6,d-2)$ is the cumulative daily return over the [-6, -2] period. $Ret(d-27,d-7)$ is the cumulative daily return over the [-27, -7] period. For stock characteristics, we have firm size, earnings-to-price ratio and monthly turnover, all measured at the end of previous month. We also use the order imbalance in previous day to control for the persistence in trading flows. To correct for potential serial correlation in the statistical inference, we compute *t*-statistics using Newey-West (1987) heteroskedastic standard errors with 5 lags.

Table IA.II presents the estimation results. For QFII, RQFII, HKC and local institutions, coefficients of $Ret(d-1)$ are -4.6313, -0.4230, -2.1991 and -1.8838, with *t*-statistics of -30.07, -0.65, -17.23 and -23.93, respectively, indicating that foreign investors as well as local institutions prefer to buy stocks when previous day's returns are low. For the relation between order flows and past week and month returns, QFIIs are still contrarian traders, while RQFII and HKC investors tend to be momentum traders. Additionally, we find that investors' order imbalances between adjacent days are significantly positive, indicating investors' trading flows are persistent to some extent.

We are curious about what firm characteristics attract foreign investors' order flow. The results show that QFII, HKC and local institutions tend to buy stocks with high earnings-to-price ratio and low turnover. Local institutions also prefer to buy large stocks, while foreign investors do no exhibit preference for firm size. RQFIIs' trading flows seem to be indifferent to firm size, EP ratio and stock turnover.

B. Predicting Risk-Adjusted Stock Returns

In this section, we examine whether foreign investors can correctly predict future risk-adjusted stock returns. We adopt the factor model in Liu, Stambaugh and Yuan (2019), which includes the market factor (*MKT*), the size factor (*SMB*), and the value factor (*VMG*), as in equation (IA2):

$$Ret(i,d) - rf(d) = \alpha(i) + \beta_{MKT}(i)MKT(d) + \beta_{SMB}(i)SMB(d) + \beta_{VMG}(i)VMG(d) + \epsilon(i,d) \quad \text{(IA2)}$$

The daily factors data is from the Stambaugh's website.[1] We estimate historical betas for each stock each day, using the previous 60 trading days observations, requiring at least 36 non-missing daily observations. We first estimate the model-implied returns $\widehat{Ret}(i,d)$. The risk-adjusted stock returns $\hat{\alpha}(i,d)$ are the difference between the raw returns and the model implied returns, as shown in equation (IA3) to (IA4):

$$\widehat{Ret}(i,d) = rf(d) + (\widehat{\beta_1}(i,d-1)MKTRF(d) + \widehat{\beta_2}(i,d-1)SMB(d) + \widehat{\beta_3}(i,d-1)VMG(d)) \quad \text{(IA3)}$$

$$\hat{\alpha}(i,d) = Ret(i,d) - \widehat{Ret}(i,d) \quad \text{(IA4)}$$

We calculate the cumulative risk-adjusted return over the window [d_1, d_2] as the difference between the cumulative raw return and cumulative model-implied return, as in equation (IA5):

$$\hat{\alpha}(i,d_1{:}d_2) = \prod_{k=d_1}^{d_2}(Ret(i,k)+1) - \prod_{k=d_1}^{d_2}(\widehat{Ret}(i,k)+1) \quad \text{(IA5)}$$

We use $\hat{\alpha}(i,\ w)$ to represent cumulative risk-adjusted return. $\hat{\alpha}(i,\ w)$ represents the weekly risk-adjusted return from $d+1$ to $d+\ 5$; when w equals 2, $\hat{\alpha}(i,\ w)$ represents the weekly risk-adjusted return from $d+1$ to $d+10$ and so on.

With the risk-adjusted return as the dependent variable, we examine foreign investors' predictive power in both short-term and long-term horizons, using the daily Fama-MacBeth (1973)

[1] https://finance.wharton.upenn.edu/~stambaug/

regression in equation (IA6) and equation (IA7), respectively.

$$\hat{\alpha}(i,d) = a0(d,G) + a1(d,G)Oib(i,d-1,G) + a2(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \quad \text{(IA6)}$$

$$\hat{\alpha}(i,w) = a0(d,G) + a1(d,G)Oib(i,d-1,G) + a2(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \quad \text{(IA7)}$$

where the main independent variable is the investor *G*'s order imbalance on previous day. All control variables are same as those in equation (2). To adjust the potential time-series autocorrelations of coefficients, the standard errors are calculated using Newey–West's (1987) methodology with five lags.

Table IA.III presents the estimation result. For short-term prediction in Panel A, the coefficients on *Oib* are positive and significant at 99% confidence level for all investor groups, meaning that both foreign investors and local institutions correctly predict next-day's risk-adjusted return. The daily interquartile risk-adjusted returns, which equals the estimated coefficient of *Oib* times interquartile range, are 0.1071%, 0.0341%, 0.0703% and 0.0877%, respectively. Based on the magnitudes, QFII is still the best, HKC is in the middle and RQFII is the weakest. QFII can perform no worse than local institutions.

Panel B presents the long-term prediction results. Take QFII as an example. The coefficient on *Oib* is 0.1037 at week 1, gradually increases to 0.2252 at week 12. The coefficients are all significant at 99% confidence level. We observe similar significantly increasing coefficients over longer periods for RQFII and local institutions. The coefficient for HKC reaches the biggest number (0.1341) at week 2 then slightly decline to 0.1030 at week 12. Overall, similar to results in Table III, foreign investors' return predictive power preserve in longer horizons.

C. Decomposition of Order Imbalance

In equation (4) we estimate Fama-MacBeth regressions to orthogonalize investors' order flows into two components: the overlapping and specific order imbalance. Table IA.IV reports estimation results of equation (4). Columns (1) to (3) present the decomposition results of foreign investors' order imbalance. We find that the coefficients of local institutions' order imbalances are significantly positive for all foreign investor groups. Column (4) shows the decomposition results of local institutions. We find significantly positive coefficients on the order imbalance of QFII and

RQFII, but a negative and insignificant coefficient on the order imbalance of HKC, suggesting that local institutions and HKC may trade stocks in different directions after controlling for order flows from QFII and RQFII. The results mean that foreign investors and local institutions' order flows do overlap, suggesting they may have common information and trade some stocks in a similar way to some extent.

D. Construct Analyst Dataset

This section describes how we construct the 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, then add new observations from the other three. To ensure accuracy, we require that the observation in final dataset be recorded in at least two of the four databases with 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 (Ivković and Jegadeesh, 2004). 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 stock-day level.

E. Compare Earnings Announcements and Analyst Activity

In Table V, we find that foreign investors are informed about firm information related to earnings announcements and analyst-related events. In this section, we examine which kind of event is more important to foreign investors' return predictive power, earnings, or analyst activity.

We estimate the following Fama-MacBeth regression:

$$
\begin{aligned}
Ret(i,d) = a0(d,G) + [&a1(d,G) + a2(d,G)TailEarnings(i,d) \\
&+ a3(d,G)NTailEarnings(i,d) + a4(d,G)TailAnalyst(i,d) \\
&+ a5(d,G)NTailAnalyst(i,d)] \times Oib(i,d-1,G) + a6(d,G)'Controls(i,d) \\
&+ \epsilon(i,d,G)
\end{aligned} \quad \text{(IA8)}
$$

where $TailEarnings(i,d)$ is equal to 1 if stock i's return on earnings day d is outside the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of all earnings day returns, and otherwise it is zero. $NTailEarnings(i,d)$ is 1 if the earnings day's return is within the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles, and otherwise it is zero. We also define the indicator variables $TailAnalyst(i,d)$ and $NTailAnalyst(i,d)$ based on whether stock i's return on analyst-related day d is outside or inside the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of all analyst-related day returns, respectively.

Table IA.V reports the results. First, for the tail and non-tail earnings days, we find insignificantly positive coefficients on the interaction terms for all investors at the 95% confidence level. In terms of analyst activity, we only find significantly positive coefficients on the interaction with the tail analyst events dummy for QFII and local institutions. HKC has a significantly positive coefficient on the interaction with non-tail analyst dummy. The results imply that QFII and local institutions have greater return predictive power on analyst events with large price movements, while HKC has stronger return predictive power on analyst events with small price movements. It seems that foreign investors as well as local institutions are more able to process analyst-related events rather than earnings announcements.

Corresponding to performance decomposition, tail earnings days make up 0.15% of the total sample, and they contribute 0.87%, 1.01%, 0.06%, and 0.68% to the overall performance of QFII, RQFII, HKC, and local institutions, respectively. Tail analyst-related event days make up 0.41% of the total sample and they contribute 1.92%, 4.57%, 0.93%, and 5.11% of the overall performance for our four investor groups. It seems that analyst-related events contribute more to investors' overall performance.

F. Robustness Tests with Event Dummy Variables

To estimate the contribution of firm information to investors' return predictability, we do not include event dummy variables in equation (7)-(8). The benefit is that we can easily connect the coefficients on interactions with investors' overall performance. However, someone might be concerned that the event dummy variables should be controlled for potential events fixed effects. To alleviate the concern, we re-estimate Fama-MacBeth regressions with event dummy variables, as shown from equation (IA9) to (IA10):

$$\begin{aligned} Ret(i,d) = a0(d,G) & \\ & + [a1(d,G) + a2(d,G)Tail(i,d) + a3(d,G)NTail(i,d)] \times Oib(i,d-1,G) \\ & + a4(d,G)Tail(i,d) + a5(d,G)NTail(i,d) + a6(d,G)'Controls(i,d) \\ & + \epsilon(i,d,G) \end{aligned} \tag{IA9}$$

$$\begin{aligned} Ret(i,d) = a0(d,G) & \\ & + [a1(d,G) + a2(d,G)TailNews(i,d) + a3(d,G)NTailNews(i,d)] \\ & \times Oib(i,d-1,G) + a4(d,G)TailNews(i,d) + a5(d,G)NTailNews(i,d) \\ & + a6(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \end{aligned} \tag{IA10}$$

The results are presented in Table IA.VI-Table IA.VII. Overall, the coefficients of the interactions and significance are very similar to regression results without event dummy variables, meaning that our findings on foreign investors' informativeness on firm information are robust.

G. Public Information Separated by Positive and Negative Stock Returns

In equation (IA11), we separate firm events days with large stock price movements into positive return days and negative return days. Then we examine whether investors have different return predictive power between positive return days and negative return days.

$$\begin{aligned} Ret(i,d) = a0(d,G) + [a1(d,G) + a2(d,G)PosTail(i,d) + a3(d,G)NegTail(i,d) & \\ + a4(d,G)NTail(i,d)] \times Oib(i,d-1,G) + a5(d,G)'Controls(i,d-1) & \\ + \epsilon(i,d,G) & \end{aligned} \tag{IA11}$$

Here, indicator *PosTail(i, d)*=1 if stock *i*'s return on event day *d* is above the 95th percentile of all event day returns, and otherwise it is zero. Indicator *NegTail(i, d)*=1 if stock *i*'s return on event day *d* is below the 5th percentile of all event day returns, and otherwise it is zero. *NTail(i, d)*=1 if stock *i*'s return on event day *d* is inside the 5th and 95th percentiles of event day returns and otherwise it is zero.

Table IA.VIII presents the regression results. For QFII, RQFII and local institutions, we find significantly positive coefficients $\widehat{a3}(G)$ at 95% confidence level, which value is larger than the coefficient $\widehat{a2}(G)$. The results imply that investors are more capable of process firm information related to negative returns.

In equation (IA12), we separate media news days with large stock price movements into positive return days and negative return days,

$$Ret(i,d) = a0(d,G) + [a1(d,G) + a2(d,G)PosTailNews(i,d) + a3(d,G)NegTailNews(i,d) + a4(d,G)NTailNews(i,d)] \times Oib(i,d-1,G) + a5(d,G)'Controls(i,d-1) + \epsilon(i,d,G) \quad \text{(IA12)}$$

Here, *PosTailNews(i, d)*=1 if stock *i*'s return on news day *d* is above the 95th percentile of all news day returns and otherwise it is zero. *NegTailNews(i, d)*=1 if stock *i*'s return on news day *d* is below the 5th percentile of all news day returns and otherwise it is zero. *NTailNews(i, d)*=1 if stock *i*'s return on news day *d* is inside the 5th and 95th percentiles of all news day returns and otherwise it is zero.

Table IA.IX presents the regression results. For all investors, we find that the coefficients $\widehat{a3}(G)$ is larger than the coefficient $\widehat{a2}(G)$, while only the coefficients for QFII and local institutions are significant. The results further suggest that investors are more capable of process firm media news related to large negative returns.

In equation (IA13), we separate days with large stock market movements into positive return days and negative return days,

$$\widehat{a1}(d,G) = b0(G) + b1(G)PosTailMarket(d) + b2(G)NegTailMarket(d) + \epsilon(d,G) \quad \text{(IA13)}$$

Here, *PosTailMarket(d)*=1 if stock market return on day *d* is above the 95th percentile of all market returns and otherwise it is zero. *NegTailMarket(i, d)*=1 if stock market return on day *d* is below the 5th percentile of all market returns and otherwise it is zero.

Table IA.X presents the regression results. In Panel A for Chinese stock market, we find that $\widehat{b1}(G)$is significantly negative for local institutions, indicating that local institutions have lower return predictive power on day when Chinese stock market experiences large positive returns. In Panel B and C, we find QFII and local institutions have significantly higher return predictive power on days when U.S or global stock market experience negative returns at 95% confidence level. All these results indicate that foreign investors may be capable of processing global market level news related to large negative market returns.

H. Macroeconomic announcements

In this section, we use macroeconomic announcements as the proxy for market level information. Following Bernile, Hu and Tang (2016), we collect U.S. macroeconomic announcements including scheduled announcements of federal funds target rate by Federal Open Market Committee (FOMC), the release of GDP growth rate by the Bureau of Economic Analysis (BEA), the release of PPI and nonfarm payroll by the Department of Labor and. To make a comparison, we select China macroeconomic news in similar categories, which include announcements of M2 growth by the People's Bank of China (PBoC), the release of GDP growth, PPI, and unemployment rate by National Bureau of Statistics (NBS). We convert U.S Eastern Standard Time to China Standard Time, then match all announcements released after Chinese stock market trading hours or in holidays to the next trading day. Our sample covers 153 and 112 U.S and China macroeconomic announcements and have 147 and 105 unique news-related trading days, respectively.

Based on these macroeconomic announcements, we define eight dummy variables, $USFOMC(d)$, $USGDP(d)$, $USPPI(d)$, $USNonfarmPayrolls(d)$,$ChinaM2(d)$, $ChinaGDP(d)$, $ChinaPPI(d)$, $ChinaUnemployment(d)$, respectively. Each dummy variable is equal to 1 when the news is released on day *d*, otherwise it is zero. Then we examine the relation between macroeconomic announcements and foreign investors' stock return predictive power:

$$\widehat{a1}(d,G) = b0(G) + b1(G)USFOMC(d) + \epsilon(d,G) \tag{IA14}$$

where the dependent variable $\widehat{a1}(d,G)$ is the time-series of coefficients on investors' order flows estimated in equation (2). The independent variable is the macroeconomic announcements dummy, such as $USFOMC(d)$ and other types of news. Significantly positive coefficients $\widehat{b1}(G)$ indicate an increase in foreign investors' return predictive power on days when macroeconomic indicators are released. The standard errors are adjusted using Newey-West (1987) methodology with 5 lags.

Panel A and Panel B in Table IA.XII present the estimation results for China and U.S macroeconomic announcements, respectively. Nearly all results are insignificant. We only find positive $\widehat{b1}(G)$ coefficients of QFII for China M2 and U.S PPI announcements, significant at 90% and 95% confidence level respectively. Local investors only have significantly higher return predictive power for China unemployment rate announcements. Overall, it seems that foreign investors' informational advantage on macroeconomic announcements are relatively limited.

I. Citigroup Economic Surprise Index

We also consider the Citigroup Economic Surprise Indices (CESI) as a proxy for macroeconomic information. The index in a specific country is built on a broad scope of economic indicators, and the weights governing each economic indicator's contribution to the index are determined by which macro surprises have the largest impact on FX markets. The indices measure how a set of economic data releases in each country compares to expectations; they rise when economic data exceed economists' consensus forecasts and fall when data falls short of expectations.

We use the CESI CNY Index as the proxy for local market information, and the CESI USD Index and the CESI G10 Index as proxies for global market information. We then investigate foreign investors' return predictive power on days with extreme macroeconomic surprises using the following two-stage regression:

$$\widehat{a1}(d,G) = b0(G) + b1(G)CESI(d) + \epsilon(d,G) \tag{IA15}$$

where the indicator variable $CESI(d)$ is equal to one if the index value falls outside the 5th and 95th percentiles of the index values in our sample, and otherwise it is zero.

Table IA.XIII presents the estimation results. In a summary, we find no evidence that foreign investors or local institutions have significantly higher return predictive power on days when CESI indices have large values, regardless of whether the surprise is on the local market or the global market. One suggestion is that the economic surprise indices are designed to capture reactions in the foreign currency market; thus, they might not reflect how equity market reacts to macroeconomic news. Consistent with our findings, it seems that foreign investors' informational advantages on market-level news are relatively muted than those of firm-level news.

Table IA.I

Trading and holding by foreign investors and local institutions conditional on stocks characteristics

This table presents the results of portfolio double sorts (independent) on firm size and earnings-to-price ratio. Our sample period is January 1, 2016, to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. In each day, we sort stocks independently into three size and three EP (all measured by the previous month-end) groups (1,2,3 indicate for small, median and large). Then we calculate the time-series average of cross-sectional mean of investors daily trading volume and holdings within each group. Panel A presents the daily average of investors' trading volume in percentage of stock daily volume; Panel B presents the daily average of investors' holdings in percentage of stock outstanding A-shares. ***, ** and * indicate significance at the 1%, 5% and 10% level from t-tests.

Panel A. Daily average trading volume in percentage of total volume

	QFII				RQFII			
	EP 1	EP 2	EP 3	Diff (3-1)	EP 1	EP 2	EP 3	Diff (3-1)
Size 1	0.51%	0.55%	0.66%	0.14%***	0.02%	0.02%	0.03%	0.01%**
Size 2	0.43%	0.56%	0.69%	0.25%***	0.03%	0.03%	0.04%	0.01%***
Size 3	0.57%	0.88%	1.22%	0.65%***	0.06%	0.10%	0.14%	0.07%***
Diff (3-1)	0.06%***	0.32%***	0.56%***		0.04%***	0.08%***	0.11%***	
	HKC				Local INST			
	EP 1	EP 2	EP 3	Diff (3-1)	EP 1	EP 2	EP 3	Diff (3-1)
Size 1	0.06%	0.10%	0.18%	0.12%***	8.16%	9.60%	11.70%	3.54%***
Size 2	0.48%	0.64%	1.04%	0.57%***	9.38%	12.12%	15.77%	6.39%***
Size 3	1.47%	2.46%	3.17%	1.70%***	13.33%	17.72%	20.99%	7.66%***
Diff (3-1)	1.41%***	2.37%***	2.99%***		5.17%***	8.12%***	9.29%***	

Panel B. Daily average stock holdings in percentage of outstanding A-shares

	QFII				RQFII			
	EP 1	EP 2	EP 3	Diff (3-1)	EP 1	EP 2	EP 3	Diff (3-1)
Size 1	0.10%	0.15%	0.18%	0.08%***	0.07%	0.04%	0.10%	0.02%***
Size 2	0.16%	0.33%	0.47%	0.31%***	0.08%	0.09%	0.10%	0.02%***
Size 3	0.48%	1.00%	1.01%	0.53%***	0.11%	0.18%	0.19%	0.08%***
Diff (3-1)	0.38%	0.85%	0.83%		0.04%	0.14%	0.10%	
	HKC				Local INST			
	EP 1	EP 2	EP 3	Diff (3-1)	EP 1	EP 2	EP 3	Diff (3-1)
Size 1	0.03%	0.04%	0.10%	0.07%***	5.69%	7.71%	8.11%	2.42%***
Size 2	0.13%	0.20%	0.33%	0.20%***	8.32%	11.69%	11.24%	2.92%***
Size 3	0.51%	1.16%	1.12%	0.61%***	12.02%	15.61%	15.33%	3.31%***
Diff (3-1)	0.49%***	1.12%***	1.02%***		6.33%***	7.90%***	7.22%***	

Table IA.II
Determinants of Order Imbalances

This table reports determinants of order flows from foreign investors and local institutions. Our sample ranges from January 1, 2016, to June 30, 2019, and consists of all stocks listed on the Main Board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate Fama-Macbeth (1973) regression. The dependent variables are scaled order imbalance measures on day *d*. The main independent variables are a series of past stock returns: *Ret(d-1)* is the stock return on the previous day; *Ret(d-6:d-2)* is cumulative daily return over the period [d-6, d-2]; *Ret(d-27:d-7)* is the cumulative daily return over the period [d-27, d-7]. We add previous day order imbalance to control the trading persistence. We add the log of market capitalization (*Lnsize*), earnings-to-price ratio (*EP*) and *Turnover* in the regression, both measured at the end of previous month. *Adj-R^2* is the time-series average of Adjusted R-squared for the first stage Fama-Macbeth cross-sectional regressions. The time-series standard errors are adjusted by Newey-West (1987) with 5 lags. We report *t*-statistics in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Oib(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Ret(d-1)	-4.6313***	-0.4230	-2.1991***	-1.8838***
	(-30.07)	(-0.65)	(-17.23)	(-23.93)
Ret(d-6, d-2)	-0.2730***	0.3219	0.2293***	0.0233
	(-4.53)	(1.43)	(5.58)	(0.73)
Ret(d-27, d-7)	-0.1218***	0.3318***	0.0418**	-0.0103
	(-4.20)	(2.97)	(2.05)	(-1.19)
Oib(d-1)	0.1299***	0.2357***	0.1346***	0.2086***
	(21.07)	(23.65)	(22.63)	(59.89)
Lnsize	0.0042	0.0011	0.0051	-0.0047***
	(0.84)	(0.13)	(1.40)	(-2.91)
EP	0.7800***	-0.2986	0.3763***	0.3226***
	(5.68)	(-0.63)	(3.52)	(4.78)
Turnover	-0.0634***	0.0770	-0.0147***	-0.0022
	(-9.92)	(1.46)	(-2.64)	(-1.49)
Intercept	-0.1545	-0.0458	-0.1007	0.0888**
	(-1.27)	(-0.22)	(-1.14)	(2.24)
Adj-R^2	8.67%	17.88%	7.15%	6.82%

Table IA.III

Risk-adjusted stock return prediction of foreign investors and local institution

This table presents the estimation results on whether foreign investors and local institutions can predict the cross-sectional risk-adjusted stock returns in both short-term and long-term horizons. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate daily Fama-MacBeth (1973) regressions. Panel A presents results on the next day's risk-adjusted return prediction, as in equation (IA6). Panel B presents the coefficients on the order imbalance measure in the w-week cumulative risk-adjusted return prediction, as in equation (IA7). 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 also control the log of market capitalization *(Lnsize)*, earnings-to-price ratio *(EP)* and monthly turnover *(Turnover)*, all measured at the end of previous month. *Adj-R^2* is the time-series average of adjusted R-squared in the cross-sectional regression. *Interquartile* is the time-series average of the cross-sectional interquartile range of the order imbalance variable. *Interquartile Return* represents the magnitude of investor's return predictability, defined as *Interquartile* multiplied by the estimated coefficient on the order imbalance. To account for potential serial correlation in the coefficients, the standard errors are adjusted using Newey-West (1987) with five lags. We report *t*-statistics in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Short-term return prediction

Dep: $\hat{\alpha}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0586***	0.0276***	0.0727***	0.1251***
	(16.07)	(3.49)	(10.30)	(18.69)
Ret(d-1)	-0.1785	-1.5076**	-0.8809	1.1319**
	(-0.37)	(-2.31)	(-1.51)	(2.24)
Ret(d-6, d-2)	-0.9627***	-0.6561**	-0.7544***	-1.2105***
	(-4.78)	(-2.32)	(-3.38)	(-6.40)
Ret(d-27, d-7)	-0.1551*	0.1025	-0.1437	-0.3139***
	(-1.69)	(0.71)	(-1.38)	(-3.64)
Lnsize	-0.0203***	-0.0089	-0.0095*	-0.0137***
	(-4.55)	(-1.20)	(-1.93)	(-2.97)
EP	0.4261	0.1651	0.0735	0.4578
	(1.12)	(0.26)	(0.18)	(1.28)
Turnover	-0.0227	-0.0990*	-0.0655***	-0.0399**
	(-1.31)	(-1.92)	(-3.32)	(-2.38)
Adj-R^2	5.57%	9.63%	5.80%	5.75%
Interquartile	1.8295	1.2342	0.9666	0.7012
Interquartile risk-adjusted return	0.1071%***	0.0341%***	0.0703%***	0.0877%***
	QFII-Local	RQFII-Local	HKC-Local	
Interquartile Return Difference	0.0194%**	-0.0535%***	-0.0183%***	
	(2.48)	(-4.96)	(-2.64)	

Panel B. Long-term cumulative risk-adjusted return prediction

Dep: Cumulative Ret(w)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Week number w	QFII		RQFII		HKC		Local INST
1	0.1037***		0.0625***		0.0917***		0.2444***
2	0.1149***		0.0985***		0.1092***		0.3202***
3	0.1331***		0.1262***		0.1217***		0.3556***
4	0.1498***		0.1256***		0.1227***		0.3735***
5	0.1462***		0.1726***		0.1093***		0.3793***
6	0.1554***		0.1703***		0.1148***		0.4163***
7	0.1779***		0.1720***		0.1315***		0.4511***
8	0.1893***		0.1865***		0.1351***		0.4916***
9	0.1828***		0.1686**		0.1067*		0.4985***
10	0.1978***		0.1959***		0.1143*		0.5122***
11	0.2110***		0.2532***		0.1193*		0.5233***
12	0.2252***		0.2529***		0.1030		0.5156***
Interquartile Cumulative Return	QFII	QFII-Local	RQFII	RQFII-Local	HKC	HKC-Local	Local INST
1	0.1898%***	0.0184%	0.0771%***	-0.0944%***	0.0886%***	-0.0828%***	0.1714%***
2	0.2102%***	-0.0144%	0.1216%***	-0.1033%**	0.1055%***	-0.1239%***	0.2245%***
3	0.2435%***	-0.0059%	0.1557%***	-0.0942%*	0.1176%***	-0.1389%***	0.2493%***
4	0.2740%***	0.0121%	0.1551%***	-0.1075%*	0.1186%***	-0.1482%***	0.2619%***
5	0.2675%***	0.0015%	0.2130%***	-0.0544%	0.1057%***	-0.1679%***	0.2660%***
6	0.2844%***	-0.0075%	0.2101%***	-0.0834%	0.1110%***	-0.1884%***	0.2919%***
7	0.3255%***	0.0092%	0.2123%***	-0.1060%	0.1271%***	-0.1968%***	0.3163%***
8	0.3463%***	0.0016%	0.2302%***	-0.1157%	0.1306%***	-0.2192%***	0.3447%***
9	0.3345%***	-0.0151%	0.2081%**	-0.1434%	0.1031%*	-0.2530%***	0.3496%***
10	0.3619%***	0.0028%	0.2418%***	-0.1190%	0.1105%*	-0.2548%***	0.3591%***
11	0.3860%***	0.0190%	0.3125%***	-0.0563%	0.1154%*	-0.2569%***	0.3670%***
12	0.4119%***	0.0504%	0.3121%***	-0.0507%	0.0995%	-0.2675%***	0.3615%***

Table IA.IV
Overlapping and specific trading decomposition

This table reports the decomposition results of overlapping and specific order imbalances for foreign investors and local institutions. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate Fama-MacBeth regressions, as in equation (4). *Adj-R^2* is the time-series average of adjusted R-squared in the cross-sectional regression. 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 the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Oib(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d, QFII)				0.0214***
				(9.25)
Oib(d, RQFII)				0.0243***
				(11.46)
Oib(d, HKC)				-0.0016
				(-0.38)
Oib(d, INST)	0.1646***	0.1388***	0.0714***	
	(19.33)	(13.56)	(7.65)	
Adj-R^2	1.06%	0.82%	1.09%	1.93%

Table IA.V

Compare investors' predictive power between earnings announcements and analyst-related events

This table presents the estimation results on whether the return predictive power of foreign investors and local institutions is related to firm earnings announcements and analyst-related events. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. Our sample covers 15,477 earnings announcements and 41,722 analyst-related events, totaling 50,331 event days. We estimate quarterly Fama-MacBeth regressions, as in equation (IA8). *TailEarnings(i, d)*=1 if stock *i*'s return on earnings day *d* is outside the 5th and 95th percentiles of all earnings day returns, otherwise it is zero. *NTailEarnings(i, d)*=1 if stock *i*'s return on earnings day *d* is within the 5th and 95th percentiles of all earnings day returns, otherwise it is zero. *TailAnalyst(i, d)*=1 if stock *i's* return on analyst activity day *d* is outside the 5th and 95th percentiles of all analyst-related day returns. *NTailAnalyst(i, d)*=1 if stock *i*'s return on analyst activity day *d* is inside the 5th and 95th percentiles of all analyst-related day returns. Control variables are same as those in equation (2). We omit coefficients of control variables and t statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0978***	0.0436***	0.0959***	0.2134***
$\widehat{a2}$: Oib(d-1)×TailEarnings (d)	0.4794	0.2702	-0.0564	0.8032*
$\widehat{a3}$: Oib(d-1)×NTailEarnings (d)	0.0235	-0.0908	0.0651	-0.1393***
$\widehat{a4}$: Oib(d-1)×TailAnalyst (d)	0.3681***	0.4750*	0.1332	2.6030***
$\widehat{a5}$: Oib(d-1)×NTailAnalyst (d)	-0.0370***	0.0418	0.0878**	0.0264
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$(Non-event)	0.1789%	0.0538%	0.0927%	0.1496%
Interquartile (Oib)× ($\widehat{a1}+\widehat{a2}$): $\widehat{Ret}2$(Tail earnings)	1.0560%	0.3873%	0.0382%	0.7128%
Interquartile (Oib)× ($\widehat{a1}+\widehat{a3}$): $\widehat{Ret}3$(Non-tail earnings)	0.2219%	-0.0582%	0.1556%	0.0519%
Interquartile (Oib)× ($\widehat{a1}+\widehat{a4}$): $\widehat{Ret}4$(Tail analyst events)	0.8523%	0.6401%	0.2214%	1.9749%
Interquartile (Oib)× ($\widehat{a1}+\widehat{a5}$): $\widehat{Ret}5$(Non-tail analyst events)	0.1111%	0.1055%	0.1776%	0.1681%
$\widehat{Ret}2$ on tail earnings days as a percentage of overall performance (0.15%)	0.87%	1.01%	0.06%	0.68%
$\widehat{Ret}3$ on non-tail earnings days as a percentage of overall performance (1.37%)	1.67%	-1.39%	2.18%	0.45%
$\widehat{Ret}4$ on tail analyst events days as a percentage of overall performance (0.41%)	1.92%	4.57%	0.93%	5.11%
$\widehat{Ret}5$ on non-tail analyst events days as a percentage of overall performance (3.68%)	2.25%	6.77%	6.70%	3.92%

Table IA.VI

Robustness test: stock return predictive power, earnings, and analyst-related events

This table investigates whether investors better predict stock returns on firm event days than non-event days with event dummy variables. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. Our sample covers 15,477 earnings announcements and 41,722 analyst-related events, totaling 50,331 event days. We estimate quarterly Fama-MacBeth regressions. In each calendar quarter, we perform OLS regression and calculate the time-series average of coefficients, as in equation (IA9). Indicator variable *Tail(i, d)*=1 if stock *i'*s return on event day *d* is outside the 5^{th} and 95^{th} percentiles of all events day returns, otherwise zero. *NTail(i, d)*=1 if stock *i'*s return on event day *d* is inside the 5^{th} and 95^{th} percentiles of events day returns, otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and *t*-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0978***	0.0440***	0.0970***	0.2120***
	(9.64)	(2.58)	(3.33)	(5.99)
Oib(d-1)×Tail(d)	0.6296***	0.8099***	0.2045	2.3867***
	(3.52)	(5.10)	(0.80)	(11.50)
Oib(d-1)×NTail (d)	-0.0339**	0.0020	0.0528	-0.0077
	(-2.16)	(0.07)	(1.54)	(-0.22)
Tail(d)	1.3757***	1.5974***	1.4899***	1.0471***
	(2.87)	(2.70)	(2.77)	(2.94)
NTail(d)	0.2353***	0.2423***	0.2622***	0.2279***
	(4.72)	(6.68)	(4.86)	(4.85)
Adj-R^2	1.34%	1.90%	1.51%	1.19%

Table IA.VII

Robustness test: stock return predictive power and media news

This table investigates the relation between investors' return predictive power and local media news, with news dummy variables. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We obtain news information from CNRDS. Our sample includes 353,551 news days accounting for 34.69% of all observations. We estimate quarterly Fama-MacBeth regressions, as shown in equation (IA10). *TailNews(i, d)*=1 if stock *i*'s return on news day *d* is outside the 5^{th} and 95^{th} percentiles of all news day returns, otherwise zero. *NTailNews(i, d)*=1 if stock *i*'s return on news day *d* is inside the 5^{th} and 95^{th} percentiles of all news day returns, otherwise zero. All control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and t statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
Oib(d-1)	0.0910***	0.0366*	0.0928***	0.1838***
	(7.16)	(1.85)	(3.39)	(5.51)
Oib(d-1)×TailNews(d)	0.4312***	0.2861**	0.2333	1.5658***
	(3.26)	(2.55)	(0.73)	(9.03)
Oib(d-1)×NTailNews(d)	-0.0131	0.0085	0.0112	-0.0429
	(-1.58)	(0.99)	(1.26)	(-1.27)
TailNews(d)	1.2390***	1.2591**	1.1337**	1.1179***
	(3.31)	(2.54)	(2.33)	(3.34)
NTailNews(d)	0.1648***	0.1085***	0.1452***	0.1789***
	(3.70)	(4.47)	(3.33)	(3.98)
Adj-R^2	3.26%	3.67%	3.29%	2.91%

Table IA.VIII

Firm events separated by large positive and negative returns

This table presents the estimation results on the relation between investors' predictive power and firm events related to earnings announcements and analyst activities. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate quarterly Fama-MacBeth (1973) regressions. We present the results on investors' return predictive power on event days versus non-event days. Indicator variable *PosTail(i, d)*=1 if stock *i*'s return on event day *d* is above the 95th percentile of all event day returns, and otherwise it is zero. *NegTail(i, d)*=1 if stock *i*'s return on event day *d* is below the 5th percentile of all event day returns, and otherwise it is zero. *NTail(i, d)*=1 if stock *i*'s return on event day *d* is inside the 5th and 95th percentiles of event day returns and otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and *t*-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. The coefficients are multiplied by 100 for readability. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0977***	0.0437***	0.0954***	0.2121***
$\widehat{a2}$: Oib(d-1)×PosTail (d)	0.2342	0.7363*	0.5087	2.0315***
$\widehat{a3}$: Oib(d-1)×NegTail (d)	0.9860***	0.9531**	0.1349	2.8057***
$\widehat{a4}$: Oib(d-1)×NTail (d)	-0.0342***	0.0292	0.0824**	-0.0042
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$(Non-event)	0.1787%	0.0539%	0.0922%	0.1487%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(PosTail)	0.6073%	0.9627%	0.5839%	1.5732%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a3})$:$\widehat{Ret}3$(NegTail)	1.9827%	1.2302%	0.2226%	2.1161%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a4})$:$\widehat{Ret}4$(Non-tail)	0.1161%	0.0899%	0.1719%	0.1457%
$\widehat{Ret}2$ on positive tail event days as a percentage of overall performance (0.245%)	0.82%	3.89%	1.47%	2.46%
$\widehat{Ret}3$ on negative tail event days as a percentage of overall performance (0.245%)	2.68%	4.97%	0.56%	3.30%
$\widehat{Ret}4$ on non-tail event days as a percentage of overall performance (4.45%)	2.85%	6.60%	7.86%	4.13%

Table IA.IX
Media news separated by large positive and negative returns

This table presents the estimation results on whether return predictive power of foreign investors and local institutions is related to local media news. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We obtain news information from CNRDS. Our sample includes 353,551 news days accounting for 34.69% of all observations. We estimate quarterly Fama-MacBeth regressions. *PosTailNews(i, d)*=1 if stock i's return on news day d is above the 95th percentile of all news day returns and otherwise it is zero. *NegTailNews(i, d)*=1 if stock i's return on news day d is below the 5th percentile of all news day returns and otherwise it is zero. *NTailNews(i, d)*=1 if stock i's return on news day d is inside the 5th and 95th percentiles of all news day returns and otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and t-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. The coefficients are multiplied by 100 for readability. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0907***	0.0327*	0.0913***	0.1849***
$\widehat{a2}$: Oib(d-1)×PosTailNews(d)	0.1687	0.2213	0.2382	0.3799*
$\widehat{a3}$: Oib(d-1)×NegTailNews (d)	0.7248***	0.4156	0.4341	2.6589***
$\widehat{a4}$: Oib(d-1)×NTailNews(d)	-0.0085	0.0163	0.0158	-0.0551
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$(Non-news)	0.0082%	0.0054%	0.0055%	0.0069%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(PosTailNews)	0.0258%	0.0096%	0.0088%	0.0345%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a3})$: $\widehat{Ret}3$(NegTailNews)	0.0470%	0.0189%	0.0323%	0.0284%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a4})$: $\widehat{Ret}4$(Non-tail news)	0.1141%	0.0277%	0.0607%	0.0892%
$\widehat{Ret}2$ on positive tail news days as a percentage of overall performance (1.73%)	4.21%	8.80%	5.13%	4.31%
$\widehat{Ret}3$ on negative tail news days as a percentage of overall performance (1.73%)	13.23%	15.54%	8.19%	21.71%
$\widehat{Ret}4$ on non-tail news days as a percentage of overall performance (31.23%)	24.07%	30.63%	30.12%	17.88%

Table IA.X

Stock market return separated by large positive and negative returns

This table presents estimation results on whether the return predictive power of foreign investors and local institutions is related to stock market movements. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. As shown in equation (IA13), we apply a two-step regression procedure. In the first step, we perform OLS regression on each day and obtain the time-series coefficients of *Oib(d-1)*, $\widehat{a1}(d)$. In the second step, we regress the estimated coefficient on the market indicator variable. *PosTailMarket(d)*=1 if stock market return on day d is above the 95th percentile of all market returns and otherwise it is zero. *NegTailMarket(i, d)*=1 if stock market return on day d is below the 5th percentile of all market returns and otherwise it is zero. Panel A, B and C present the second-step regression results with the Chinese stock market proxy, the US stock market proxy and the global stock market proxy, respectively. The standard errors are adjusted using Newey-West (1987) with five lags. To spare the space, we omit t statistics in the table. The coefficients are multiplied by 100 for readability. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Dep: $\widehat{a1}(d)$	(1)	(2)	(3)	(4)
	QFII	RQFII	HKC	Local INST
Panel A. The Chinese stock market				
$\widehat{b0}$: Intercept	0.0673***	0.0276***	0.0754***	0.1378***
$\widehat{b1}$: PosTailMarket (d)	-0.0185	-0.0118	0.0098	-0.1006***
$\widehat{b2}$: NegTailMarket (d)	-0.0297	0.0463	0.0480	0.0032
Panel B. The US stock market				
$\widehat{b0}$: Intercept	0.0624***	0.0255***	0.0724***	0.1310***
$\widehat{b1}$: PosTailMarket (d)	-0.0188	0.0636	0.0572	-0.0476
$\widehat{b2}$: NegTailMarket (d)	0.0533**	0.0269	0.0651*	0.1157***
Panel C. The global stock market				
$\widehat{b0}$: Intercept	0.0627	0.0247	0.0750	0.1300
$\widehat{b1}$: PosTailMarket (d)	-0.0048	0.0509	0.0220	-0.0444
$\widehat{b2}$: NegTailMarket (d)	0.0506**	0.0391	0.0532	0.1076**

Table IA.XI

Stock return predictive power and large stock price changes

This table presents estimation results on whether return predictive power of foreign investors and local institutions is related to stocks with large price changes. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We estimate quarterly Fama-MacBeth regressions. Panel A presents the results on investors' return predictive power on days with large stock price changes Panel B presents results on whether public firm information contributes to investors' predictive power on days with large stock price changes. *TailDay(i, d)*=1 if the return for stock *i* on day *d* is outside the 5th and 95th percentile of all sample returns, otherwise zero. *TailDayInfo(i, d)*=1 if stock *i* on large stock price change day *d* has an earnings announcement, analyst-related activity, or media news, otherwise it is zero. *TailDayOther(i, d)*=1 if no earnings, analyst-related events and media news happens for stock *i* on large price change day *d*, otherwise it is zero. Control variables are same as those in equation (2). To spare the space, we omit coefficients of control variables and *t*-statistics in the table. To account for serial correlation in the coefficients, the standard errors of the estimated coefficients are adjusted using Newey-West (1987) with five lags. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. Stock return predictive power on large stock price change days

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0683***	0.0346**	0.0742***	0.0868***
$\widehat{a2}$: Oib(d-1)×TailDay(d)	0.3512***	0.1827	0.3636**	1.2889***
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$	0.1249%	0.0427%	0.0717%	0.0609%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(Large price change day)	0.7673%	0.2683%	0.4232%	0.9647%
$\widehat{Ret}2$ on large price change days as a percentage of overall performance (10%)	40.57%	41.08%	39.60%	63.78%

Panel B. Stock return predictive power on large price change days with public firm information

Dep: Ret(d)	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{a1}$: Oib(d-1)	0.0683***	0.0346**	0.0742***	0.0870***
$\widehat{a2}$: Oib(d-1)×TailDayInfo (d)	0.3514***	0.2668*	0.3344	1.4114***
$\widehat{a3}$: Oib(d-1)×TailDayOther (d)	0.3562***	-0.0280	0.3668***	1.1639***
Interquartile (Oib)× $\widehat{a1}$: $\widehat{Ret}1$	0.1249%	0.0427%	0.0717%	0.0610%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a2})$: $\widehat{Ret}2$(Large change with information)	0.7678%	0.3719%	0.3949%	1.0507%
Interquartile (Oib)× $(\widehat{a1}+\widehat{a3})$: $\widehat{Ret}3$(Large change with others)	0.7766%	0.0081%	0.4263%	0.8772%
$\widehat{Ret}2$ on large price change days with information as a percentage of overall performance (4.77%)	19.31%	31.37%	17.83%	33.21%
$\widehat{Ret}3$ on large price change days with others as a percentage of overall performance (5.23%)	21.42%	0.75%	21.10%	30.40%

Table IA.XII
Stock return predictive power and macroeconomic announcements

This table investigates the relation between investors' stock return predictive power and scheduled macroeconomic announcements. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. Following Bernile, Hu and Tang (2016), we collect U.S. macroeconomic announcements including scheduled announcements of federal funds target rate by Federal Open Market Committee (FOMC), the release of GDP growth rate by the Bureau of Economic Analysis (BEA), the release of PPI and nonfarm payroll by the Department of Labor and. To make a comparison, we select China macroeconomic news in similar categories, which include announcements of M2 growth by the People's Bank of China (PBoC), the release of GDP growth, PPI, and unemployment rate by National Bureau of Statistics (NBS). We convert U.S Eastern Standard Time to China Standard Time, then match all announcements released after Chinese stock market trading hours or in holidays to the next trading day. Our sample covers 153 and 112 U.S and China macroeconomic announcements and have 147 and 105 unique news-related trading days, respectively. Then we define eight dummy variables, $USFOMC(d)$, $USGDP(d)$, $USPPI(d)$, $USNonfarmPayrolls(d)$,$ChinaM2(d)$, $ChinaGDP(d)$, $ChinaPPI(d)$, $ChinaUnemployment(d)$, to represent these macroeconomic announcements respectively. Each dummy variable is equal to 1 when the news is released on day *d*, otherwise it is zero. The regression is specified in equation (IA14). Standard errors are calculated by Newey-West (1987) of 5 lags and *t*-statistics are in the parentheses.

Panel A. China macroeconomic announcements

Dep:$\widehat{a1}(d)$	(1)	(2)	(3)	(4)
	QFII	RQFII	HKC	Local INST
ChinaM2(d)	0.0257*	0.0488	0.0368	0.0101
	(1.70)	(1.59)	(1.42)	(0.32)
ChinaGDP(d)	-0.0274	-0.0511	-0.0185	0.0082
	(-0.90)	(-0.97)	(-0.41)	(0.23)
ChinaPPI(d)	0.0128	0.0287	0.0302	0.0013
	(0.80)	(0.69)	(0.98)	(0.04)
ChinaUnemployment(d)	-0.0336	0.0222	0.0717	0.0637*
	(-0.90)	(0.44)	(1.01)	(1.84)

Panel B. U.S macroeconomic news days

Dep:$\widehat{a1}(d)$	(1)	(2)	(3)	(4)
	QFII	RQFII	HKC	Local INST
USFOMC(d)	-0.0433	0.0323	0.0125	-0.0341
	(-1.50)	(0.82)	(0.40)	(-0.76)
USGDP(d)	0.0052	0.0340	-0.0071	-0.0012
	(0.27)	(1.04)	(-0.24)	(-0.04)
USPPI(d)	0.0271**	-0.0310	0.0225	-0.0299
	(2.03)	(-0.89)	(0.80)	(-1.00)
USNonfarmPayrolls(d)	-0.0310	-0.0599	0.0280	-0.0420
	(-1.53)	(-1.26)	(0.84)	(-1.25)

Table IA.XIII

Stock return predictive power and Citigroup Economic Surprise Index

This table presents estimation results on whether the return predictive power of foreign investors and local institutions is related to macroeconomic surprise. Our sample period is January 1, 2016 to June 30, 2019, and our sample includes common stocks listed on the main board of Shanghai Stock Exchange (SSE) with at least fifteen non-zero volume trading days in the previous month. We use Citigroup Economic Surprise Indices (CESI) of China (CNY), U.S (USD) and G10 countries (G10) as proxies for macroeconomic surprise. Indicator variable *CESI(d)*=1 if on day d the index is outside the 5^{th} and 95^{th} percentile of the entire sample distribution, otherwise zero. As shown in equation (IA15), we apply a two-step regression procedure. In the first step, we perform OLS regression on each day and obtain the time-series coefficients of *Oib(d-1)*, $\hat{a}_1(d)$. In the second step, we regress the estimated coefficient on the CESI indicator variable. Panel A, Panel B and Panel C present the second step regression results when we use CESI CNY Index, CESI USD Index and CESI G10 Index as the macroeconomic surprise proxy, respectively. The standard errors are adjusted using Newey-West (1987) with five lags. To spare the space, we omit *t*-statistics in the table. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Panel A. CESI CNY Index

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0663***	0.0286***	0.0763***	0.1329***
$\widehat{b1}$: CESI (d, CNY)	-0.0125	0.0121	0.0200	-0.0078
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$	0.1212%	0.0354%	0.0738%	0.0932%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Large surprise)	0.0983%	0.0503%	0.0931%	0.0877%
$\widehat{Ret}2$ on large surprise days as a percentage of overall performance (10%)	8.26%	13.65%	12.30%	9.47%

Panel B. CESI USD Index

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0669***	0.0285***	0.0788***	0.1357***
$\widehat{b1}$: CESI (d, USD)	-0.0194	0.0128	-0.0049	-0.0234
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$	0.1224%	0.0351%	0.0761%	0.0951%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Large surprise)	0.0869%	0.0509%	0.0714%	0.0787%
$\widehat{Ret}2$ on large surprise days as a percentage of overall performance (9.65%)	7.04%	13.41%	9.11%	8.12%

Panel C. CESI G10 Index

Dep: $\widehat{a1}(d)$	(1) QFII	(2) RQFII	(3) HKC	(4) Local INST
$\widehat{b0}$: Intercept	0.0632***	0.0297***	0.0794***	0.1328***
$\widehat{b1}$: CESI (d, G10)	0.0177	0.0014	-0.0121	0.0023
Interquartile (Oib)× $\widehat{b0}$:$\widehat{Ret}1$	0.1157%	0.0367%	0.0767%	0.0931%
Interquartile (Oib)× $(\widehat{b0}+\widehat{b1})$:$\widehat{Ret}2$(Large surprise)	0.1481%	0.0384%	0.0651%	0.0947%
$\widehat{Ret}2$ on large surprise days as a percentage of overall performance (10%)	12.46%	10.42%	8.61%	10.16%