Information Glitters: Follow Northbound Investors on China's Interconnected Market*

Keqi Chen Yuehan Wang Xiaoquan Zhu

First version: April 2019

This draft: August 2019

* The authors are with PBC School of Finance, Tsinghua University. Keqi Chen: chenkq.16@pbcsf.tsinghua.edu.cn. Yuehan Wang: wangyh.16@pbcsf.tsinghua.edu.cn. Xiaoquan Zhu: zhuxq.16@pbcsf.tsinghua.edu.cn. We are grateful to Li An, Zhuo Chen, Lauren Cohen, Zhiguo He, Alan Huang, Sida Li, Bibo Liu, Clark Liu, Dong Lou, Hongfeng Peng, George Wang, Neng Wang, Xian Wang, Jianfeng Yu, Hong Zhang, Hao Zhou, Haoxiang Zhu and seminar and conference participants at PBCSF Tsinghua University and SUFE for valuable suggestions and comments. We are responsible for all remaining errors. Send correspondence to Xiaoquan Zhu, PBC School of Finance, Tsinghua University, 43 Chengfu Road, Haidian, Beijing, China, 100083. E-mail: zhuxq.16@pbcsf.tsinghua.edu.cn.

Information Glitters: Follow Northbound Investors on China's Interconnected Market

This draft: August 2019

ABSTRACT

This paper explores a persistent mechanism through which investors profit from the potential information contained in capital flows from northbound investors on the interconnected market. Using a complete history of daily filings about stock-level holdings among all northbound investors, we document that weekly changes in northbound shareholdings (HPC) have a positive cross-sectional predictability for future stock returns. A long-short portfolio that exploits this differentiating preference earns abnormal returns of up to 61 basis points per week, which cannot be explained by common factors. In addition to flow pressure derived from copycat herding among domestic investors, we also show evidence that HPC has stronger predictability around earnings announcements in firms with more overseas business income, confirming that northbound investors are more likely informed on the interconnected stock market. Moreover, after the "penetrating" supervision on northbound investor identity started in September 2018, the cross-sectional return predictability shows sign of decay, suggesting that some of northbound investors are probably domestic funds that make round-trip investment on A shares to hide identity of majority shareholders and potential information advantage. Besides, time-series analysis reveals that northbound capital is a short-term predictor of market returns both in and out of sample. We also observe similar cross-sectional predictability for H-share returns in southbound investors' trading behavior.

JEL Classification: G10; G12; G14

Key words: Copycat herding, Informed trading, Interconnected markets, Northbound flows, Round-trip investment

1 Introduction

The stake of China's stock market was almost zero for international institutional investors that are more likely to have insider information before the policies of QFII and RQFII were made. However, China has taken a number of steps over the recent years to encourage international use of its currency, most notably with the launch of the Shanghai/Shenzhen-Hong Kong Stock Connect Scheme, a cross-border equity trading link denominated in RMB. The Shanghai-Hong Kong Stock Connect Scheme first launched on 17 November 2014. Based on this successful pilot project, China Securities Regulatory Commission and Hong Kong Securities and Futures Commission jointly announced that Shanghai-Hong Kong Stock Connect Scheme would be officially launched on December 5, 2016. Bypassing regulation on positions in spot foreign exchange, it allows international and mainland's domestic investor to trade securities anonymously in each other's markets through local trading and clearing facilities. All Hong Kong and international investors are allowed to trade eligible A-shares listed in the mainland's exchanges while only the mainland's domestic investors who have at least RMB 500,000 in their cash-and-investment accounts are eligible to trade Hong Kong-listed shares.

With the liberalization of financial market, the benefits of accessing China's A-share Stock Market become increasingly attractive to both international investors and academic researchers. Since Chinese government has launched many new policies during the reform of financial system in the last two decades, China is a good laboratory for financial studies. In summary, there are five streams of research on China's stock market: the privatization of SOEs, political connections of firms, regulatory environment, A-H cross-listed stocks and the role of China's stock market in the global market (Shan et al., 2018). Although the literature is large, the following important questions are missing: Do northbound/southbound investors profit from the trading across markets? What information can we infer by investigating the changes in shareholdings through the Stock Connect Scheme? Are the northbound/southbound capital flows smart money with information advantage? Can capital flows driven by the informed trading be an effective predictor for the market return? Therefore, this paper attempts to fill the gap by investigating the information contained in capital flows and trading behaviors through the mutual market.

Most previous studies use the pilot project on Shanghai Stock Exchange as a quasi-natural experiment and argue that the Stock Connect Scheme introduces a demand shock for A-share markets.

For example, Zhong and Lu (2018) suggest that the Stock Connect Scheme improves the efficiency of the process of information being incorporated into asset prices on the A-share market through analyst covering and corporate governance optimization. During the announcement of the scheme, connected stocks experienced revaluations due to demand shock and speculative trading (Liu, Wang and Wei, 2018). However, our understanding about informed trading and information edge among northbound investors from empirical research is still rather limited. In this paper, we propose a measure of the weekly percentage changes in shareholdings among all northbound investors scaled by outstanding shares (HPC) at the stock level. Intuitively, the measure provides a view about the informed trading of northbound investors involving the relatively high frequency variation of their preferences for specific securities. Based on this measure, we aim to better understand the information content of international and institutional investors' holding, in particular, the nexus of northbound trading, copycat herding and information advantage.

Our empirical analysis provides four sets of results. First, we show that HPC significantly predicts future returns of connected stocks on the A-share market. Stocks in the highest HPC decile outperform those in the lowest decile by 0.61% per week (t-value = 2.99). The cumulative excess returns of hedge portfolio show no evidence of reversal in the subsequent eight weeks after formation. It suggests that northbound investors may be informed about firm fundamentals and if any, stock mispricing beyond demand pressure. The stock-level increase in HPC is associated with short-term reversal, high volatility, low idiosyncratic risk, low turnover, high ROA and an addition to MSCI indices. Most of these preferences among northbound investors are consistent with the definition of White Horse Unit, characterized by high level of information transparency and profitability margin. The return predictability holds in a bunch of robustness checks, including subsamples across exchanges and over time, Fama-Macbeth cross-sectional regressions and double sorting on size and northbound ownership.

Second, we show evidence of three channels through which informed trading profit is realized. One is information advantage among northbound investors, and another is domestic investors masquerading as international funds to make round-trip investment, and the third one is flow pressure induced by copycat herding[1]. On the one hand, HPC predicts cumulative abnormal returns (CARs)

[1] For the term "round-trip investment", we borrow the language from the economic geography research (See, for example, Fung et al, 2011; Ledyaeva et al., 2015). In the economic geography research, round-trip investment is commonly identified as the round-tripping of capital from emerging economies to offshore financial centers and back as foreign direct investment. Based on the previous work, the round-tripping is more likely driven by the regulatory arbitrage and secrecy arbitrage, namely, hiding their true identities from authorities in the home location). Here rather than revisit the link between demand regulatory arbitrage and "foreign" direct investment on the real

around quarterly earnings announcements (QEAs). The CARs increase over time with the release of fundamental information to the public. Additionally, the pattern driven by information edge is stronger in firms with more overseas business income, about which are more likely informed by foreign investors. On the other hand, after the "penetrating" supervision on northbound investor identity was implemented from September 2018, the cross-sectional return predictability of HPC shows sign of decay, suggesting that some of northbound investors are probably domestic ones that make round-trip investment on A shares to hide identity of majority shareholders. They may masquerade as northbound investors who can take advantage of lack of oversight on northbound investor identity on the Hong Kong Exchanges to gain access to invisible shareholdings and prevent private information from being disclosed to the public through their unusual trading. However, portfolios sorted by herding measure using a subsample of stocks on the most actively traded lists deliver long-run return reversal, though we do observe an attractive return predictability in the first week. It suggests that we cannot rule out the contribution to return predictability of flow pressure induced by copycat herding following northbound investors.

Third, in the time-series regressions, we document that the net inflow of northbound capital through the Stock Connect Scheme is a reliable signal at a weekly frequency. The strong predictability is statistically and economically significant both in and out of sample. It even enhances portfolio performance as shown in the time-series analysis. The underlying information advantage postulates a positive effect of northbound flows on future returns. Besides, noise traders may herd in and out of the market to engage in the northbound-trading-following strategy and pump up the asset price. Therefore, the implication of the copycat herding is also consistent with a momentum effect of northbound flows on future returns.

Finally, the return predictability is also observed in HPC among southbound institutional investors. We find striking evidence that the predictability power comes most from Mainland China's companies listed on the Hong Kong Stock Exchange. Taking as given that southbound institutional investors are more likely informed about the firms with local connection, the powerful return predictability in this subsample would be expected. This finding further supports our hypothesis related to information

economy—the focus of prior work in this area—our focus is "foreign" stock investment on the emerging capital market. We define the "round-trip investment" as the domestic funds which pretend to be northbound investors and trade A shares indirectly through Hong Kong trading accounts on the interconnected market.

advantage. Besides, we find no evident decay of return predictability of southbound HPC after September 2018 when the exchanges started the penetrating supervision on northbound investors, which is in sharp contrast with the striking decay of northbound predictability. If it is the case that there are incentives for domestic investors to make round-trip investment and hide identity, then the result would be expected because of ongoing regulatory requirements of personal identification numbers assigned to each investor on the domestic market.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 outlines channels through which weekly percentage changes in shareholdings among northbound investors predict future stock returns and develops our main hypotheses. Section 4 presents the empirical analysis. Section 5 performs robustness tests. Section 6 concludes the paper.

2 Related Literature

Our paper adds to a large literature examining how information becomes incorporated into asset prices and its effect on market efficiency (e.g., Ben-Rephael et al., 2017; Edelen, Ince and Kadlec, 2016; Grossman and Stiglitz, 1976; Engelberg, McLean and Pontiff, 2018). Engelberg, McLean and Pontiff (2018) find that anomaly returns are driven by biased expectations of sentimental investors and much higher around earnings announcements. Ben-Rephael et al. (2017) argue that institutional demand for information is associated with a risk premium and the correction of mispricing given the presence of limited attention on the market. Besides, arbitrageurs are effective in detecting mispricing (Shleifer and Vishny, 1997; Sias, Turtle and Zykaj, 2015; Jiao, Massa and Zhang, 2016). The return predictability of their trading is consistent with information advantage and the subsequent copycat trading of other types of institutional investors (Chen, Da and Huang, 2018). Based on the literature, our paper documents that if institutional investors are informed about the firm fundamentals and mispricing, then abnormal return of informed trading would be expected due to the release of firm-level news and the correction of mispricing.

Several papers document that the motivations of buying behaviors are quite different between individual and institutional investors (Barber and Odean, 2008; Barber, Odean and Zhu, 2009). Barber and Odean (2008) find that attention-based purchases by individual investors could temporarily inflate stock prices and then lead to lower subsequent returns, while professionals are likely to employ explicit purchase "criteria", especially for the value-strategy institutional investors. Their paper differs from ours in many respects. They focus on identifying daily attention-grabbing events using trading volume, return, and news sorts; we, on the stock lists with most actively traded securities. The attention-driven buying patterns they document do not generate superior returns; the copycat trading in our setting contributes to the return predictability. They test and confirm the hypothesis that preferences determine choices after attention has determined the choice set. On the contrary, we argue that in our setting of China's interconnected stock market, attention determines the individual investors' choice after institutional investors' preferences have determined the choices set.

Since the laboratory we exploit is that of interconnected stock markets in China, our paper is also relevant to a recently emerging literature studying the impact of market openness on the stock price. A strand of literature explores whether the interconnection between the A-share and H-share market can improve the quality and efficiency of information impounded into price (Liu, Wang and Wei, 2018; Shan et al., 2018; Zhong and Lu, 2018; Zhong et al., 2018). There is mixed evidence on the change of pricing efficiency, market correlation and stock revaluation related to the launch of the Stock Connect Scheme. For example, Liu, Wang and Wei (2018) find that the connected stocks experience significant higher returns in anticipation of positive demand shocks from Hong Kong investors and the interaction between demand shocks and speculative trading through mutual market access results in stock mispricing (Liu, Wang and Wei, 2018). However, Zhong and Lu (2018) and Zhong et al. (2018) argue that the scheme damps the spillover effect of market volatility as well as the price synchronicity due to international investors' informed trading and enhanced oversight. Besides, Shan et al. (2018) show that the connected stocks are not vulnerable to financial contagion of the price volatility on the global market due to market openness and China's stock market can provide valuable diversification benefits for international investors. Hence, it is not obvious that whether the interconnected market is efficient and investors can profit from informed trading with access to each other's markets. Rather than revisit the link between demand shocks and improved market openness—the focus of prior work in this area—our key contribution in this paper is to analyze the implications for asset prices of informed and copycat trading induced by foreigners' information edge and domestic investors' imitative herding, respectively. In this way, our paper concentrates on the pricing implications of northbound capital flows, along with its market predictability and potential learning behaviors following northbound investors' informed trading behaviors. We show that HPC significantly predicts stock returns both in the short and long run. Additionally, the trading strategy (i.e. return predictability) appears to continue to be effective over time due to "create-space effect" driven by copycat herding as well as the release of information on the interconnected market, though the market openness might improve the pricing efficiency through introducing international investors, at least partially.

The long standing literature are consistent with a common story in which domestic and foreign investors have different preferences for stock characteristics and show different reactions to public information (Froot and Teo, 2008; Jia, Wang and Xiong, 2017). In recent years, a prevailing view in finance is that on average, domestic investors outperform foreign institutions due to their trading pattern and stock picking skills consistent with local information edge (e.g., Agarwal et al. (2009) in Indonesia; Choe et al. (2005) in Korea; Dvořák (2005) in Indonesia; Ferreira et al. (2017) in 32 countries; Hau (2001) in Germany; Shukla and Van Inwegen (1995) in the United States; Teo (2009) in Asia; Zou, Tang and Li (2016) in the Mainland China). However, many studies hold the opposing view that sophisticated foreign investors may have a particular advantage over local investors through global private information that they have acquired in their own market (e.g., Bailey et al. (2007) in Singapore and Thailand; Brennan and Cao (1997) in the U.S.; Chen et al. (2009) in Taiwan; Choe, Kho and Stulz (1999) in Korea; Froot and Ramadorai (2008) in 25 countries; Froot et al. (2001) in emerging markets; Grinblatt and Keloharju (2000) in Finland; Huang and Shiu (2009) in Taiwan; Maffett (2012) in the cross-country setting; Seasholes (2000) in Thailand and Taiwan). For example, Choe, Kho and Stulz (1999), find that Korean domestic institutions generally follow, rather than trade against, foreign investors. Most of these studies conclude that the degree of investors' sophistications matters in determines which type of market participants would play a leading role in disclosing potential information to the market and counterparties[2].

To the best of our knowledge, our paper is the first to use the daily stock-level shareholdings among northbound investors in China's interconnected stock markets to identify foreign investors' informed trading. Our measure, HPC not only has cross-sectional predictability for stock returns, but also facilitates the time-series predictability of market return at the aggregate level. Moreover, we find that the outperformance of stocks suffering copycat herding are more likely to reverse in the long run, even though they attract more international investors in the short run. This provides an intuitive link between the limited attention and copycat trading following informed and sophisticated investors. Besides, we

[2] See Ferreira et al. (2017) for a more comprehensive literature review.

show some evidence that there is a possibility that domestic funds pretend to be northbound investors and then take advantage of lack of oversight on northbound investor identity prior to the implementation of Northbound Investor ID model on 17 September, 2018. In this way, our tests shed light on how northbound investors trade on the mutual market and how their trading behaviors affects asset prices through news and attention.

3 Hypothesis development

The section raises the question of why net purchases by foreign investors are associated with higher future returns. One possibility that has not been explicitly examined is that the positive correlation between northbound inflows and future returns may reflect superior information of Hong Kong and foreign investors that is impounded into prices through their informed trading. This argument warrants further research in our setting, but seems not unlikely, given the perceptions of many existent studies that foreigners should be expected to have an informational advantage over domestic investors in emerging markets (e.g., Bailey et al. (2007); Chen et al. (2009); Froot et al. (2001); Huang and Shiu (2009); Seasholes (2000)). Along the same line, northbound investors may be sufficiently sophisticated to uncover information about firm fundamentals, which enable them to identify the mispriced stocks exactly as well as predict the market reactions to firm-level news.

Intuitively, we can rule out the possibility that much of the cross-sectional variance in daily net inflows from foreigners into domestic stock markets would be a simple story of demand shocks. If northbound investors' trading decisions are purely speculative, we should not observe a cross-sectional variation considering the positive demand shocks of universal application for connected stocks. In this case, we may not observe any incremental relation between northbound investors' increasing shareholdings and stock future returns, controlling for flow pressure driven by the contemporaneous changes in net inflows, or we may observe a reverse effect if northbound investors are trade-imbalance-sensitive in their speculative response to market openness. Either of these results is potentially consistent with the proposed explanation for demand shocks' revaluation effect observed in prior studies (e.g., Edelen and Warner (2001), Goetzmann and Massa (2003); Liu, Wang and Wei (2018); Richards (2005)). If we do observe a persistent return predictability of northbound investors' increasing shareholdings to future returns, this would support the notion that foreign investors' preferences with respect to their informational advantage drive their trading decisions. We thus form our first hypothesis about the return predictability with informed northbound investors.

Hypothesis 1: *The changes in shareholdings among northbound investors (HPC) should positively predict future stock return beyond flow pressure due to the information advantage of foreign and Hong Kong investors.*

Northbound traders may be sufficiently sophisticated to uncover information about firm fundamentals, which enable them to identify the mispriced stock exactly as well as predict market reactions to firm-level news (Chen, Da, and Huang (2018), Jiao, Massa, and Zhang (2016)). For example, Chen, Da, and Huang (2018) document that long-short portfolio returns during earnings announcement window are three times larger than periods without announcement. Similar with them, we compare the cross-sectional returns during normal time and event periods to investigate whether northbound investors utilize the information edge. We also show in later sections that northbound investors can forecast cumulative abnormal returns (CARs) around quarterly earnings announcements (QEAs), which allows them to benefit from the market reaction.

There is widespread anecdotal evidence that mainland funds tend to be channeled to Hong Kong and make round-trip investment on A shares[3]. There may be a mixture of motives, such as lower transaction fees on the interconnected market, lower commission of Hong Kong brokers and especially, lightly regulated investor identity system. The authority failed to supervise the northbound investor identity until Hong Kong Exchanges and Clearing Limited (HKEX) launched the investor identification model for Northbound trading through its mutual stock market access on 17 September 2018[4]. In other words, if some mainland funds masquerade as northbound investors to gain access to large shareholdings, then only the Hong Kong Securities Clearing Company (HKSCC) would appear on the list of top ten largest shareholders. There would not be any detailed information about investor identity disclosed to the public, and thus it may obfuscate exact ownership and prevent the potential information contained in the invisible shareholdings from being exploited by the public. Since September 2018, exchange participants that offer northbound trading services are required to assign a unique number in a standard format, known as the Broker-to-Client Assigned Number, to each of their

[3] See, for example, http://www.sohu.com/a/15894607_114351 for anecdotal evidence about round-trip investment of domestic funds on the interconnected market.

[4] See the website of HKEX https://www.hkex.com.hk/Mutual-Market/Stock-Connect?Sc_lang=en for more details about the northbound investor identification model. Broker-to-Client Assigned Numbers and Client Identification Data are for regulators' market surveillance only and not released.

Northbound trading clients and provide Client Identification Data to HKEX, which will forward the information to Mainland exchanges. If it is the case that some mainland investors try to make full use of their information edge without drawing regulators' scrutiny and copycat herding and this channel contributes to the return predictability of HPC, then there would be evident sign of decay in predictability after September 2018 due to the launch of northbound investor identification model. We thus form our second hypothesis.

Hypothesis 2: *The changes in shareholdings among northbound investors (HPC) may positively predict A-share return partially due to the information advantage of some mainland investors that hide identity, disguise themselves as northbound investors and make round-trip investment.*

Note that Broker-to-Client Assigned Numbers and Client Identification Data - the two main components of the Northbound Investor Identification Model - are for regulators' market surveillance only and not released. Based only on the decay of return predictability after September 2018, we cannot rule out the possible compounding factors. To show further support to our second hypothesis, we also do a placebo test related to the regulation effect on the cross-sectional predictability of changes in shareholdings among southbound investors. Due to ongoing supervision on mainland investor identity, it would be expected that for the implantation of the Northbound Investor Identification Model, there may be no evident effect on the H-share return predictability which is more driven by southbound investors' information advantage on Mainland China's companies.

Testing Hypothesis 1 and 2 in the cross-section requires us to justify the presence of information edge in the northbound investors. It is empirically difficult, however, to separate stock price movement driven by copycat trading among imitative investors and active trading among informed investors due to unavailable account-level data on the interconnected stock market. However, in our paper, rather than aiming to rule out the prevalence of flow pressure, we try to justify the contribution of imitative herding to cross-sectional return predictability. It is well documented that foreign investors are frequently viewed as being closely watched and influencing stock prices in emerging economies characterized by relative illiquidity in previous studies (e.g. Richards, 2005). Regardless of which stock they select to invest in, northbound inflows as well as imitative flows from other investors would help boost the stock price of large equity positions in northbound investors. Along the same line, low expected return in the group with the largest decrease in northbound holdings might be partially attributed to potential “fire sales” driven by northbound informed selling and local investors’ imitative herding to liquidate these shares. The rationale leads to our third hypothesis.

Hypothesis 3: *The copycat herding by other investors could also contribute to the return spread between extreme groups of stocks sorted by HPC in northbound investors*.

Even though we find no support for return reverse in the long run in the entire sample, the decay of return predictability would be expected in a subsample of stocks facing flow pressure caused by excessive investor attention. In other words, when we narrow our focus to the subsample which is more likely affected by copycat trading, a return reverse should be observed in the long run following an attractive abnormal return in the short run.

4 Empirical Results

4.1 Data and Summary Statistics

We draw from a range of data sources to construct the sample we use in this paper. We obtain the complete history of daily A-shares held by all northbound investors and daily lists of Top 10 daily most actively traded stocks (i.e. Top 10 stocks with the highest trading volume in RMB) from Hong Kong Exchanges and Clearing Limited (HKEX). We collect data related to aggregate northbound capital flows from WIND database. We also obtain daily stock returns, risk-free rate, analyst information and firm-level financial characteristics from China Stock Market Trading Research (CSMAR) and Choice database.

Since the list of eligible shares in the connect scheme follows the adjustment of constituent stocks in specific indices, we track all the eligible A-share stocks no less than once in history to address the potential concern on the survivor bias. We drop stock-week observations with purchasing constraints due to the index reconstitution based on the record data of sample stocks in the CSMAR database. The final sample includes 1795 A-share stocks, spanning from March 2017 to December 2018. Considering the transaction asynchronism on the interconnected market, we keep only stock-week positions when a specific stock is tradable for northbound investors. To address the potential noise in the weekly return due to share suspension, we delete the weeks with less than two trading days. Note that at the beginning of the available data, the Stock Connect Scheme has already opened up both Shanghai and Shenzhen A-share markets to international investors and removed the aggregate quotas for limiting the cumulative net purchasing value of northbound flows.

We propose a measure to capture the average trading behaviors of northbound investors on individual A-share stocks. Specifically, weekly changes in northbound shareholdings for stock i in week t, namely *HPC*, is defined as the difference in the ratio of northbound holding to the total shares outstanding between the end of week t and week $t\text{-}1$:

$$HPC_{it} = \frac{Shares\ of\ Stock\ i\ held\ by\ northbound\ investors\ in\ week\ t}{Total\ shares\ outstanding\ of\ Stock\ i\ in\ week\ t} - \frac{Shares\ of\ Stock\ i\ held\ by\ northbound\ investors\ in\ week\ t-1}{Total\ shares\ outstanding\ of\ Stock\ i\ in\ week\ t-1}$$

For example, if the reported holding percent of stock *i* at the end of week *t-1* and week *t* is 10% and 20%, respectively, then HPC_{it} is 10%. We would argue that this measure contains more information than the growth rate of shareholdings among northbound investors. Taking the numeric example above, if stock, j, experiences an increase of holding percent from 1% to 2% among northbound investors, then both stock *i* and *j* have a growth rate of shareholdings 100%. However, the HPC for stock *i*, 10%, is much larger than that for stock i, 1%. Intuitively, the weekly change in stock *i*' s position contains more information related to northbound investors' preference.

[Table 1 about here]

Table 1 presents the summary statistics of stock-level variables. Panel A focuses on key variable of interest, *HPC* and control variables including level of positions among all northbound investors (HP), log of market capitalization (Size, in thousand RMB), the book-to-market ratio (BM), the gross profits-to-assets ratio (ROA), return volatility computed as the standard deviation of daily excess market return over the past 3 months (VOL), idiosyncratic volatility computed as the standard deviation of residual from 3-month Fama-French three-factor regressions on daily data (IVOL), turnover (TURN), stock return reversal computed as the cumulative return from week t −4 to week t – 1 (REVERSAL) and stock return run-up computed from week t-52 as of the end of week t-5 (RUNUP)[5]. There are 1795 unique A-share stocks and 117,598 stock-week observations in the final sample. Several striking features in summary statistics are worth discussing. First, the average A-share holding ratio is 0.61% in northbound investors, suggesting that the northbound capital only accounts for the minority of A-

[5] Details of the sample and variable construction are provided in the Appendix.

share investors. Second, note that the median size of all eligible A shares is about 16.52 billion RMB on the interconnected stock market, while the median size of all A-share firms is 4.1 billion RMB at the end of 2018. The gap means that the majority of A shares on the mutual market are large firms, which is more likely to be selected as eligible assets for the Stock Connect Scheme.

Panel B of Table 1 reports the summary statistics of decile portfolios sorted by weekly HPC. At first glance, the average HPC in different groups has a wide range from -0.21% to 0.26%. However, the number does not actually change much over from Group 2 to Group 9. In other words, much of the cross-sectional variation comes from the difference between extreme deciles. Furthermore, level of positions among all northbound investors (HP) are not even distributed among decile portfolios. More specifically, both the extreme groups have higher HP than other groups. So intuitively, the cross-sectional return predictability is more of an informational story, rather than holding pressure. Even though the size of the extreme groups is slightly larger than that of other groups, there is not much between-group difference for other common characteristics such as the IVOL, VOL and BM ratio.

4.2 Cross-Sectional Return Predictability of HPC

In this section we present empirical results linking the strategy based on weekly HPC in northbound investors to A-share future performance. First, we conduct standard univariate portfolio sorts as well as Fama-MacBeth (1973) regressions to examine whether changes in northbound shareholdings are associated with stock future price. We show that the cross-sectional return predictability, which cannot be explained by common factors and DGTW adjustment, is robust across exchanges and over time. The sub-period analysis implies that investors may learn from the trading strategy beyond typical price pressure. Second, we confirm that the cross-sectional predictability of HPC to subsequent stock return is robust to a variety of settings with different formation and holding period. Especially, the return spread between extreme groups sorted by HPC does not reverse in the long run. Third, we show evidence that much of the variance in HPC as well as the excess return of high-minus-low portfolio cannot be completely explained by lagged returns and a bunch of common stock characteristics.

4.2.1 Univariate Portfolio Sorts

We sort all eligible stocks into decile portfolios based on HPC at the end of each week and then evaluate value weighted returns in each decile for the following week. Following the practice in the literature, we also use the Carhart (1997) four-factor model to assess the benchmark adjusted performance of stock portfolios. In order to gauge the economic magnitude of return predictability, we estimate return spreads between the top- and the bottom-decile portfolios and conduct statistical significance tests using the heteroscedasticity and autocorrelation consistent (HAC) GMM estimator for each group.

[Table 2 about here]

Panel A, B and C of Table 2 report excess returns, Carhart (1997) four-factor alphas and DGTW (1997) benchmark-adjusted returns, in percent per week, of the stocks in decile portfolios sorted by their weekly HPC, respectively. At the end of each week all stocks are sorted into deciles based on their HPC using the previous week of data. The portfolios are held for one week. Then the monthly value-weighted portfolio returns are calculated within each decile. A high-minus-low strategy using the extreme deciles, 1 and 10, with a long position in the high-HPC decile and a short position in the low-HPC decile, is then constructed. As shown in Panel A, a long-short portfolio that exploits northbound investors' preference earns abnormal returns of up to 61 basis points per week, or almost 31.72 percent per year. The striking pattern with respect to the significant return spread between extreme groups remains in the quintile portfolios as well as the halves. The return difference cannot be explained by common factors in the Carhart (1997) four-factor models, including the market factor, SMB, HML and the momentum factor. More specifically, the four-factor alpha spread between extreme deciles is about 51 basis points per week, which is economically and statistically significant at the 1% level. There is just a slight decrease in return spread between top and bottom decile sorted by HPC when using characteristic-based benchmarks. In Panel D of Table 2, our results are similar if one week is skipped after sorting to ensure that all the data is available at portfolio formation. We find that the main results are quantitatively similar.

One drawback of the univariate portfolio sorts is that they do not allow for a multivariate analysis. However, it is well documented by the long standing literature that many firm-level characteristics can successfully predict stock returns on the cross-section, such as size, Book-to-Market ratio and past stock returns. So in Table 3, we run Fama-MacBeth (1973) regressions to confirm that the lagged return as well as a variety of firm characteristics cannot subsume the cross-sectional return predictability of HPC. Table 3 reports results of the second stage of Fama-MacBeth (1973) regressions. Model (1) only includes our key variable of interest and Model (2) contains firm-level characteristics and returns within different horizons. One potential concern is that northbound investors just position themselves based on the same sample of companies used in MSCI indices. Hence, we add to the model, MSCI, a dummy variable which identifies the component stocks in the index and obtain similar results. Model (3) also controls contemporaneous HPC to exclude the effect of capital flow pressure if any. In all model specifications, our coefficient of interest remains significantly positive. The results from Fama-MacBeth regressions provide evidence that the strong positive link between changes in northbound shareholdings and future stock return is likely derived from the information advantage northbound investors have.

[Table 3 about here]

Table 4 examines the variation of cross-sectional predictability across market and over time. In Panel A, we repeat univariate sorts for subsamples of firms listed on Shanghai and Shenzhen Stock Exchange, respectively. All qualitative inferences from Table 2 remain unchanged, although the predictability is slightly weaker on the Shenzhen Stock Exchange. Panel B reports the results for the two sub-periods. During the first sub-period from March 2017 to January 2018, the return spread between extreme groups with the largest increase and decline in HPC is only statistically significant at the 10% level. In sharp contrast, the results for the more recent sub-period as of the end of 2018 show that the value-weighted average return in the High group is significantly larger than that in the Low group at the 1% level. The evidence from the sub-period analysis is consistent with investor learning over time. On the one hand, northbound investors appear to differentiate between “good” and “bad” stocks in the recent sub-period due to learning more about firm fundamentals. On the other hand, local A-share investors might learn about the preferences of northbound investors as well as the potential profits from copycat herding that coincides with the popularity of such a trading strategy.

[Table 4 about here]

4.2.2 Does Return Predictability Reverse in The Long Run?

In this section, we try to confirm that the cross-sectional predictability of HPC to subsequent stock return does not reverse in the long run. Though the stock-level data in our paper say nothing about the investor-level trading behaviors of foreigners, we show evidence that cumulative positive returns of the long-short portfolio are beyond flow pressure even in the most extreme hypothetical scenarios.

[Table 5 about here]

Panel A of Table 5 reports the accumulative excess return of hedge portfolios in different lengths of formation and holding period. For example, when the number of formation weeks equals one and the number of holding weeks equals eight, the underlying assumption is that northbound investors trade based on the HPC in one week and do not position themselves in the subsequent eight weeks. At the end of the holding period, the average cumulative return spread between extreme quintile portfolios over eight weeks following formation is up to about 1.58% and statistically significant at the 1% level. If we take another extreme case where northbound investors construct their portfolios based on HPC each week, then both the number of formation weeks and holding weeks equals one. We can see from the top left hand corner of Table 5 that the most active strategy would deliver an average weekly return of up to 50 basis points, or almost 4% per eight weeks. Taking the potential trading costs into account, the magnitude of the most active strategy's net return is still likely large than 1.58%. In other words, although we cannot figure out whether northbound investors tend to hold portfolios long enough or scramble to position themselves frequently, the return predictability shows no reversal in the long run.

Following Jegadeesh and Titman (1993), to more accurately simulate real-world trading behaviors, we also adopt a similar design to test for the long-run performance of portfolios with overlapping holding periods based on changes in northbound shareholdings. More specifically, a strategy that selects stocks on the basis of HPC over the past J weeks and holds them for K weeks is constructed as follows: At the beginning of each week t, the eligible stocks on the interconnected market are ranked in ascending order on the basis of their HPCs in the past J weeks. Based on these rankings, five quintile portfolios are formed. In each week t, the trading strategy buys the top quintile portfolio and sells the bottom quintile portfolio, holding this position for K weeks. In addition, the strategy closes out the position initiated in month t - K. Hence, under this trading strategy we revise the weights on 1/K of the stocks in the entire portfolio in any given week and carry over the rest from the previous week. Panel B of Table 5 reports the profits of the above strategies for a series of portfolios that are rebalanced weekly to maintain equal weights.

To construct a single time series spanning the entire sample period, we concatenate the top- and bottom-quintile portfolio returns as well as hedge portfolios across the holding week. Figure 1 plots the cumulative excess return spanning from March 2017 to December 2018 if northbound investors adopt the J=1 / K=1 strategy. Overall, a steep downward slope in the bottom quintile portfolios' cumulative excess returns as well as an upward slope in the top quintile portfolios s' cumulative excess returns generates a striking upward slope in the long-short strategies. Thus, Figure 1 provides strong support for the sustainable return predictability as well as the constant investor learning.

[Figure 1 about here]

4.2.3 Determinants of changes in northbound shareholdings

Before exploring the information channel through which changes in northbound shareholdings have price implications in the cross-section of stocks, we would like to understand the characteristics of stocks with different HPC. We run a set of panel regressions to investigate which of determinants plays an important role in explaining the cross-sectional differences in stock returns.

[Table 6 about here]

Panel A and B of Table 6 report results of panel regressions of HP and HPC on firm characteristics, respectively. All regressions include year-month and industry fixed effects and cluster standard errors by industry. In Panel A, we find a strong positive relation between stock return run-up, gross profitability, the addition to the MSCI China index, analyst covering and HP as well as a strong negative relation between the Book-to-Market ratio, turnover and HP. The result suggests that northbound investors prefer past "winners" with high-quality profits, growth potential and rich information environment, rather than assets with more noise trading. However, the R^2 statistics across all specifications are relatively small, no more than 26%, suggesting that in addition to firm fundamentals, there may be other reasons involving with information for northbound preference.

Panel B presents the potential determinants of key variable of interest, HPC. Although the determinants are only slightly different between HP and HPC, the R^2 statistics for HPC are much smaller than that for HP. Informally, this is suggestive of an explanation where northbound investors respond more to information advantage than to lagged returns related to market inefficiency as well as common fundamental factors to detect profit margins and position themselves. Since one concern is that northbound capital flows might be purely value investors tracking assets with these firm characteristics like "White Horse Unit", our analysis of portfolio sorts is repeated by using HPC residuals of specification (1) in Panel B of Table 6. The results, reported in the Appendix, are quantitatively similar to those based on the original value of HPC.

4.3 Hypothesis 1: Information Advantage

In this section, we take three steps to show evidence of information advantage among northbound investors. First, if northbound investors indeed trade based on firm's intrinsic value information, they would act like mispricing correctors and earn return spread between underpriced and overpriced assets, with the anticipation that stock prices would tend towards the equilibrium in the long run. Accordingly, we track the excess return spread between extreme groups sorted by changes in northbound shareholdings and examine whether these informed investors profit from information release. Second, we show that northbound investors could forecast abnormal returns around quarterly earnings announcements so as to benefit from stock market reaction. Third, taking as given that northbound investors are more likely informed about firms with more overseas business income, a stronger pattern driven by information edge is expected in those firms in double sorting.

4.3.1 Cross-Sectional Returns around Information Release

Fundamental information release is a crucial channel through which public news would affect stock prices, especially in Chinese stock market where limits to arbitrage induce severe mispricing. In Mainland China, only a group of eligible stocks are approved in margin trading and short selling. Although northbound investors are permitted to short selling in the Shanghai/Shenzhen-Hong Kong Stock Connect Scheme, few eligible stocks have ever been shorted by northbound investors, as reported in HKEX. In the investment environment lacking in effective mechanisms of price discovery, the communication between firms and market plays a critical role in guiding security price adjustment. In this case, investors who trade in the direction of information by advance would achieve substantial returns when potential information is released to the public gradually.

[Table 7 about here]

In Table 7, we track the excess return spread between extreme quintile portfolios sorted by changes in northbound shareholdings. In Column 1, we examine the cross-sectional stock returns over a five-day window around quarterly earnings announcements. To be comparable with main results in Table 5, we also compute the cumulative excess returns from one to eight weeks following announcement dates. The weekly return spread between extreme groups reaches 0.52% (t-value=3.30) over the five-day window, higher than the average stock return spread of 0.50% (t-value=3.31) per week over the entire sample (as reported in the top left corner of Panel A in Table 5). Besides, the cumulative return of long-short strategy increases with the release of firms' fundamental information along the subsequent weeks. More specifically, the cumulative excess return is up to 2.31% (t-value=5.10) as of the end of the eighth week after announcements, much larger than 1.58% (t-value=3.81) in the case without earnings announcement (as reported in the top right corner of Panel A in Table 5). In other words, there is even no significant decay in return spread when extending the horizon. Importantly, the absence of return reversal in the long run suggests that the cross-sectional predictability is not purely driven by temporary flow pressure induced by imitative trading among other investors.

Note that, such return spread between extreme quintile portfolios sorted by HPC mainly comes from the bottom groups, rather than the top ones in Table 7. It is different from the return pattern in periods without earnings news as reported in Table 5. It appears to suggest that the disclosure of firm earnings is more likely to unveil the real value of stocks that have been overestimated by uninformed investors. Once the fundamental information is available to the public, stock prices adjust downward to the reasonable level. In those cases, informed northbound investors succeed to avoid future loss by reducing their shareholdings in mispriced stocks in advance.

4.3.2 HPCs Forecast CARs and SUEs around QEAs

If they are well informed, then northbound investors would increase their shareholdings on the stocks with the anticipation of positive abnormal returns around quarterly earnings announcement. To do this, the average daily performance of the cross-sectional trading strategy in a 20-day window around firm's earnings announcement dates is plotted in Figure 2. At the beginning of each trading day, we sort eligible stocks into quintile portfolios based on their HPCs calculated one day before. A high-minus-low strategy using the extreme quintiles, with a long position in the top-HPC quintile and a short position in the bottom-HPC risk quintile, is then constructed. The hedge portfolios are held for one day. "0" on the x-axis denotes the day of earnings announcement and y-axis represents daily high-minus-low returns in hedge portfolios. It appears that increases in northbound shareholdings line up well positive abnormal returns around QEAs.

[Figure 2 about here]

In formal tests, short-term market reaction to announcements is measured as the buy-and-hold abnormal return adjusted by market model over a five-day window [-2, +2], where the market benchmark is defined as the value-weighted portfolio of all A-share stocks listed on Shanghai or Shenzhen exchange[6]. Estimation window is required to be one year [-376, -11] for each stock, with minimum observations of 90 trading days. Following Livnat and Mendenhall (2006), standard earnings surprises (SUEs) are defined as: $SUE_{i,t} = \frac{X_{i,t}-X_{i,t-4}}{P_{i,t}}$, where $X_{i,t}$ denotes earnings per share for firm i in quarter t. The key variable of interest is a variant of the ranking variable, changes in northbound shareholdings (HPC), calculated as the difference of holding ratio between t-1 and t-6, where t is the first day of event window. Control variables include firm and stock characteristics.

Table 8 presents a bunch of panel regressions forecasting the BHARs and SUEs around QEAs. The dependent variables are SUE and CAR [-2, +2] across all specifications in Panel A and Panel B, respectively. Column (1) presents results for the base model with industry and quarter fixed effect. Column (2) examines institutional ownership, column (3) considers analyst covering and column (4) estimate the full specification. As shown in the Table 8, the coefficient estimates of HPC are positive and statistically significant at 5% across all specifications. It strongly confirms our hypothesis that northbound investors tend to increase their shareholdings before others without information advantage, when they anticipate the earning growth or positive abnormal returns around quarterly earnings announcements.

[Table 8 about here]

4.3.3 Double Sorts

If the main arguments about the presence of information advantage holds, then it appears to be a natural inference that northbound investors are more likely informed about firms with more overseas business income which may help establish linkages of information exchange between domestic firms and foreign investors. Then, a stronger cross-sectional predictability driven by information edge would be expected in those firms. Many other motivations and effects, including tax incentives (Azémar et al., 2007) and corporate governance and external supervision optimization (Aggarwal et al., 2011;

[6] In untabulated tables, we also employ Fama-French three factor model and constant model as alternative benchmarks to estimate abnormal returns during the announcement window, and the main pattern remains quantitatively similar.

Zhong and Lu, 2018), can potentially lead to the price implication of foreign investors on the interconnected stock market. In the current study, overseas business income is simply used as a proxy for a source of information, and this paper does not model or investigate possible underlying forces which lead to build overseas connections in the first place or which affect ex post pricing efficiency. Instead, this paper focuses on the effect of information intensity on the cross-sectional predictability of HPC.

To study whether a HPC characteristic contains unique information on stock future return, we first report the results for double portfolio sorts with respect to HP in Panel A of Table 9. We sort the sample stocks by their stakes in northbound investors into two groups and next each group is sorted to quintile portfolios by HPC. We find that both return spreads are positive and statistically significant at 1% in both below-median and above-median HP groups suggesting that our key variable of interest, HPC, contains unique information that do not depend on shareholding situation. Hence, the double sorts indicate that the effects of the characteristics can be decoupled and changes in northbound shareholdings are a more significant driver of stock future price. This result is actually consistent with those related to potential determinants of HP and HPC, as reported in Table 6. Again, it indicates that even though northbound investors may have particular investment preferences, for example, specific industries, the variation of changes in shareholdings are not directly proportional to historical positions driven by passive rebalancing.

[Table 9 about here]

The results for double sorts with respect to A-H cross-listing are presented in Panel B. If they have information advantage on the interconnected market, then northbound investors are more likely informed about cross-listed firms because they are at least with knowledge of H-share market. It would be expected that trading behaviors of northbound investors have more cross-sectional predictability for cross-listed firms. The results confirm our conjecture with a larger return spread in the subgroup of cross-listed firms, up to about 0.81% (only about 0.43% in the rest group). Along the same line, the return spread between extreme quintiles is positive and statistically significant in only above-median overseas-business-income group, as shown in Panel C of Table 9. The difference of return spreads between below-median and above-median groups sorted by overseas business income is positive and statistically significant at 5%. It suggests that trading behaviors of northbound investors within one week have more cross-sectional predictability for firms with larger overseas business income. The results can be rationalized because northbound investors are more likely informed about firms with the stronger connection with international investors and economic conditions given their familiarity with overseas markets. More specifically, we can interpret it as a trading strategy that ideally, if most of information edge among northbound investors comes from firms with more overseas business income, then they could earn a weekly return up to 0.53% by entering into the long-short portfolio sorted by HPC within the above-median group and lighten a position of hedge portfolio constructed within the below-median group.

Furthermore, based on the double sorting results related to overseas income, we repeat the analysis about HPCs forecasting SUEs and CARs around QEAs in both below-median and above-median-overseas-income groups. Panel B of Table 8 reports the results. We can see from the table that in the above-median group, HPC of northbound investors have a stronger predictability for earning growth and abnormal stock return around earning announcements. The difference of coefficient estimates between above- and below-median group is positive and statistically significant at 10% across most regressions. It suggests that for firms with higher overseas income, northbound investors are more likely to have information edge and increase their shareholdings when they anticipate good fundamentals before formal earning announcements.

4.3.4 Further Tests Related to Changes in Southbound Shareholdings

We also examine the cross-sectional predictability of southbound capital flows for H-share stock returns in Table 10. Consistent with our informational hypothesis, changes in southbound shareholdings can also positively predict the future stock return. In the whole sample of connected H shares, the return spread between extreme quintile groups sorted by weekly changes in southbound shareholdings on individual H share is up to about 64 basis point per week. Furthermore, as shown in Panel A, most predictability comes from southbound informed trading in firms with Chinese capital or Mainland background listed on the H-share market. It is not surprising, because southbound investors, most of which are domestic institutional investors, are more likely informed about firms with more connection with the Chinese Mainland market. Along the same line, we find no long-run reversal in Panel B, suggesting that beyond price pressure, southbound investors are informed about firm fundamentals and if any, stock mispricing.

[Table 10 about here]

4.4 Hypothesis 2: Round-Trip Investment

One might concern that *some* of northbound investors are actually mainland funds that make round-trip investment on A shares, rather than foreigners that make cross-border investment. However, it is important to recognize that the round-trip investment may be also motivated by information advantage and thus it can contribute to the cross-sectional return predictability. In Panel C of Table 9, we show evidence that in the above-median group sorted by the amount of overseas income, the return spread between extreme quintiles sorted by northbound HPC is significantly large. However, in untabulated tables, we find no similar pattern in double sorts with respect to the proportion of overseas income in total income. Furthermore, we report the summary statistics for stock portfolios sorted by HPC in the subgroup of firms with positive overseas income in Panel C of Table 1. We can see that the relation between HPC and the proportion of overseas income in total income is nearly flat, while the amount of overseas income and HP increase almost monotonically with HPC. Taken together, there may be possibility that in firms with higher overseas income, executives exploit their inside information to make round-trip investment on their own stocks on the A-share market using a majority of foreign-currency earnings from their business through the interconnected markets. The stock connect scheme tends to be haven for regulation on this type of insider trading prior to the construction of investor identification system.

[Table 11 about here]

One caveat of the above analysis is that it is unclear who is behind the northbound trading. However, to our best knowledge, the authority did not collect details about investor identity until the launch of Northbound Investor Identification Model[7]. In this section, we examine the potential effect of regulation change on the round-trip investment. Panel A and B of Table 11 reports the results of cross-sectional predictability of northbound and southbound HPC for the two sub-periods, respectively. The first sub-period spans from March 2017 to August 24, 2018 when HKEX scheduled the rollout of the investor identification model for northbound trading in Stock Connect Scheme, and the second one

[7] See, for example, https://www.hkex.com.hk/-/media/HKEX-Market/Mutual-Market/Stock-Connect/Reference-Materials/Northbound-Investor-ID-Model/NB-Investor-ID-Information-Paper-Chi.pdf?la=zh-HK for more details about regulation on northbound investor identity.

from September, 2018 to the present[8]. In Panel A, the return spread between extreme groups sorted by northbound HPC is statistically significant at the 1% level before the announcement of investor identification regulation. However, the results for the more recent sub-period show sign of decay in terms of cross-sectional predictability. It suggests that the launch of northbound investor identification model plays an important role in hamstringing potential round-trip investment driven by inside information on the interconnected market. We expect that the appetite for hiding identity may be gravely diminished among mainland funds pretending to be northbound investors because implementation of the northbound investor identification model would result in more efficient cross-border market surveillance.

In Panel B of Table 11, we show further evidence with a placebo test examining the potential effect of regulation change on the return predictability of changes in southbound shareholdings. If it is more of a compounding factor related story, for example, changes in the market structure of the Stock Connect Scheme over time, rather than changes in regulation on northbound investor identity, then the sign of decay in return predictability of changes in southbound shareholdings would be also expected during the more recent sub-period. However, the result, the even larger return spread for the second sub-period, in Panel B rejects the conjecture and support the story related to regulation arbitrage. Because there have been strict regulations governing the identification of southbound investors on the mainland exchanges from the outset, southbound trading is more likely driven by information edge, rather than hide identity to accumulate position. Hence, it can be rationalized that the added regulations on the identification of northbound investors have no diminished effect on the return predictability.

4.5 Hypothesis 3: Copycat Herding

In the analysis testing Hypothesis 1 above, we actually rule out one concern that the return predictability is solely driven by flow pressure on stock price. In other words, it can scarcely be that there is no information advantage at all and some of northbound investors anticipate the copycat trading among the rest of northbound investors as well as domestic noise traders. However, we cannot rule out the possibility that other investors would imitate trading behaviors among some northbound investors with information edge. Then the imitative herding flows from other investors would help

[8] Here we divide the sample weeks based on the announcement date of Northbound investor identification model, i.e., August 24, because it would be expected that once the plan for regulation change is announced to the mutual market, northbound investors may respond to it by reducing round-trip investment and insider trading. 2018. In untabulated tables, we also repeat our main analysis using the launch date, i.e., September 26, 2018.

boost the stock price in the subsequent weeks, at least partially.

As reported in Table 5, we show evidence of no return reversal on average in the long run in the entire sample. In this section, to figure out the presence of flow pressure driven by imitative herding, we narrow our sample to a subgroup of securities which are more likely affected by investor attention, i.e., stocks on the daily most actively traded lists. It is well acknowledged that these stocks tend to attract more media coverage and public attention. For anecdotal evidence, the apps, such as FT Chinese and The Wall Street Chinese, share the news feed of such lists of Top 10 most actively traded stocks every trading day. Moreover, major data providers like WIND and CSMAR database, all report data related to the subgroup of stocks on the lists, however, none of them reports data related to northbound shareholdings. It is natural that these stocks on the daily lists are more likely affected by imitative herding flow and hence exhibit a reversed pattern of stock return in the long run[9].

To test this, we use the subsample of stocks on daily lists to construct the quintile portfolios based on the weekly herding measure in a two-week rolling window[10]. Adapted from Cai et al. (2019), Lakonishok, Shleifer and Vishny (1992), Wermers (1999), our volume-based herding measure is defined as

$$VBHD_{i,t} = \frac{purchases_{i.t} - sales_{i,t}}{purchases_{i,t} \ + \ sales_{i,t}}$$

where $purchases_{i.t}$ and $sales_{i,t}$ denote the buying and selling of stock i of northbound investors within week t, respectively. We repeat our analysis of Table 5 in this subsample and Panel A of Table 12 presents results[11]. We find that quintile portfolios sorted by the herding measure $VBHD$ using a subsample of stocks deliver a long-run return reversal, though we do observe an attractive positive return spread between extreme portfolios in the short run. The return spread slightly increases in the first three weeks from ranging 0.67% to 0.89%, and then decrease monotonically from 0.77% at the end of the forth week to almost zero as of the end of the eighth week. The gradual decay of cross-sectional predictability suggests that flow pressure driven by copycat herding following northbound investors also contributes to return predictability.

---

[9] In untabulated analysis, we drop the stocks on the lists and repeat our main analysis in Table 2 (univariate sorts) and Table 5 (different formation and holding periods). The results are quantitatively similar.

[10] We use a two-week rolling window to make sure that we have enough stocks on the lists to construct effective portfolios each time a ranking is performed based on the herding measure. In untabulated results, the main pattern shown in Table 11 is robust to different lengths of sample window.

[11] The public data only separate the purchases from the sales in the trading volume data on daily lists of Top 10 most actively traded stocks. For the rest of sample, we can only obtain the aggregate net shareholdings of all northbound investors at the stock level.

[Table 12 about here]

Due to limitations in account-level data, it is empirically difficult to distinguish the potential price pressure from (some) northbound capital flows from that from copycat herding of domestic investors. In our paper, we provide only suggestive evidence on the source of flow pressure by tracking the cumulative changes in shareholdings among northbound investors. Panel B of Table 12 presents the results. There is no pronounced increasing trend in the difference of HPC between the top- and bottom-quintile portfolios during the following weeks after formation. These results can help address the potential concern on the presence of herding within the group of northbound investors and attribute more flow pressure to copycat trading following northbound capital flows among domestic investors without information edge. Moreover, the average autocorrelation of degree one of weekly HPC is quite low (about -0.134), which validates this measure as legitimate candidates for northbound investors' response to information, rather than stale preference. We also examine the potential daily herding behavior in Panel C and D of Table 12. Because there is an inevitable one-day lag between daily changes in northbound shareholdings and investor response to the information, we investigate the subsequent four days after the ranking day within each trading week. As shown in Panel C, investors buying into the trend of HPC is relatively persistent within week while the short-side herding following the decreasing of northbound shareholdings reverse quickly as of the one day after sorting. We can see from Panel D that the order of pre-ranking herding measure is kept within the week, though the herding spread decreases gradually in the next four days. It also indicates that aggregate herding behaviors last for at least one week.

4.6 Time-Series Predictability of HPC

In this Section, we explore the time-series predictive ability of northbound capital flows on the market returns. We document that the net inflow of northbound capital is a reliable signal at weekly frequency. The outstanding predictability is statistically and economically significant both in and out of sample, and robust under the sub sample analysis. More importantly, a trading strategy based on the model prediction generates substantial profits for investors.

4.5.1 In-sample and out-of-sample prediction

We use the amount of net inflows from northbound investors (denominated in RMB yuan) to predict future market returns in Mainland China. Specifically, we investigate three aggregate-level predictors: the net purchase of total northbound capital through Shanghai/Shenzhen-Hong Kong stock connect (NetAmt_North), the net purchase of northbound capital through Shanghai-Hong Kong connect (NetAmt_SH), and the net purchase of northbound capital through Shenzhen/Hong Kong connect (NetAmt_SZ). In our paper, three market indices are to be predicted: value weighted portfolio of all A shares (AllAShares), value weighted portfolio of A shares in Shanghai stock market (SHZA), and value weighted portfolio of A shares in Shenzhen stock market (SZAZ). Available data sample is longer for analysis in this section, spanning from November 2014 to December 2018, which provides us with sufficient observations of 210 weeks to estimate the effective parameters.

We apply the commonly used univariate predictive regressions for in-sample forecasting as follows:

$$R^e_{t+1} = \alpha + \beta NetInflow_t + \varepsilon_{t+1}$$

where R^e_{t+1} is the market return in excess of the risk-free rate at week t+1, $NetInflow_t$ is the lagged net inflow of northbound capital. Here our interest is that how well the model fits with real values, so we focus on the in-sample R^2. We also examine the out-of-sample predictive power of net inflows from northbound capital. As documented in Goyal and Welch (2008), out-of-sample test is more relevant for evaluating return predictability in real time as it avoids the over-parameterization issue. In line with Goyal and Welch (2008), Han and Li (2017), we adopt a recursive estimation scheme for out-of-sample forecasts using the following single-predictor model:

$$\mathrm{E}_t(R^e_{t+1}) = \alpha_t + \beta_t NetInflow_t$$

where α_t and β_t are estimated recursively using data from the first week to week t.

The initial estimation period is from November 2014 to December 2015. To figure out whether the predictability is stable over time, out-of-sample performance is evaluated in three sub-samples: January 2016 to December 2018; January 2017 to December 2018; January 2018 to December 2018. We compare the model forecasts with historical average ones through two widely used statistics, i.e., R^2_{OS} and annualized certainty equivalent return.

[Table 13 about here]

Table 13 presents the forecasting results. As shown in Panel A, in-sample R^2 exceeds 2% in most cases. Considering that any single predictor hardly beats the historical benchmark on Chinese stock market, our results indicate that net inflows from northbound capital is a potentially useful predictor for excess market returns. Panel B provides more striking evidences. Both NetAmt_North and NetAmt_SH deliver positive R_{OS}^2 for out-of-sample tests. Especially, NetAmt_North generates consistently superior predictive power for AllAShares, with R_{OS}^2 ranging from 3.48% to 6.37%, which is surprisingly high under such a simple model specification. As for economical implications, Panel C shows that an investor who balances portfolio between a risk-free asset and the market portfolio according to model forecast rather than historical mean, could achieve significant utility gains. For example, when predicting returns of AllAShares using NetAmt_North, investors could obtain annualized profit gain of 19.09% during January 2016 to December 2018, 24.31% during January 2017 to December 2018, and 42.81% during January 2018 to December 2018. Overall, we show evidence that net inflows of northbound capital predict market returns in and out of sample. In many cases, it contributes to enhance investment performance to take into account the information contained in northbound capital flows.

4.5.2 Market Timing Strategy

To shed more lights on the time-series predictability, referring to Han and Li (2017), we propose a simple market timing strategy. The design of the strategy is as follows: At the end of each week, investors would take a long position of the market return over the next week, if he or she receives a buying signal. Otherwise, investors would liquidate the risky market portfolio and then use the proceeds to invest in the risk-free asset. The trading signal is identified based on the out-of-sample predictions as illustrated in Section 4.5.1. When the predicted excess market return is positive, it is defined as a buying signal. For brevity, we only report the results of one predictor and one market index, i.e., using the net purchases of total northbound capital (NetAmt_North) to predict the returns of value-weighted portfolio of all A shares (AllAShares). Returns of buy-and-hold strategy are set to be the benchmark. Additionally, to investigate the predictability under different horizons, holding periods range from one to eight weeks. We use the methodology suggested by Jegadeesh and Titman (1993) with overlapping portfolios to derive the time series of the weekly returns for all holding periods larger than one week. Out-of-sample evaluation period spans from January 2016 to December 2018.

Panel A in Table 14 reports annualized excess returns (in percent) and annualized Sharpe ratio for the benchmark as well as the timing strategy. As it stands, the simple buy-and-hold strategy incurs a loss, with negative annualized excess return of -5.28% and negative Sharpe ratio of -0.29. In contrast, our proposed strategy yields remarkable profits. In the case of one-week holding period, the annualized return is up to 12.83%, associated with large positive Sharpe ratio of 0.82, significantly outperforming the benchmark. Looking across the different holding periods, excess return reaches the highest when holding the original position for three weeks. In addition, it seems that the forecastability of net inflows from northbound capital mainly exists in the short run from one week ranging to five weeks, which confirms our argument that the northbound capital is an important signal for the short-term market return. Panel B in Table 13 provides more evidence by estimating the risk-adjusted alphas of investment strategies based on Carhart (1997) four-factor model. We report the results of the benchmark and the timing strategy where the holding period is one week. As anticipated, our proposed strategy earns more significant and larger risk-adjusted return of 0.22% per week, relative to the insignificant risk-adjusted return of 0.01% generated by the buy-and-hold strategy.

[Table 14 about here]

To sum up the time-series analysis, net inflows of northbound capital has outstanding predictability for market returns and its forecasting power can be translated into enormous economic gains.

5 Robustness Check

We perform a bunch of robustness tests to determine whether the main findings are sensitive to our research design. Some of these tests have been mentioned or footnoted throughout the text; others are discussed here or reported in the Appendix. First, to address the concern on estimation errors in extreme groups, we repeat univariate portfolio sorts using the back-tested procedure suggested by Mamaysky et al. (2008) in Table I.1 of the Internet Appendix. The cross-sectional predictability of HPC is even more salient in the back-tested sample. Second, in Table I.2, we examine daily HPCs and find that the cross-sectional predictability is robust to a trading strategy based on the variation of shareholdings among northbound investors at the highest possible frequency. Finally, to determine whether northbound flows are purely value investors tracking “good” assets without any motivation driven information advantage, our analysis of portfolio sorts is repeated by using HPC residuals after a bunch of firm-level characteristics, as reported in Table I.3.

6 Conclusion

There is mixed evidence on the relative performance and information advantage of foreign investors and local institutional investors in the long-standing literature. It also highlights the difficulty of separating informed trading based on *some* foreign investors' information advantage about future growth and mispricing from copycat trading among other noise traders. Empirically, in the current study, we show evidence that both northbound investors and southbound institutional investors perform well in using the information advantage and the changes in their holdings have a relatively persistent predictability for stock return on each other's market though the stock connect scheme beyond the price pressure. Our main findings related to northbound investors' information edge as well as their outperformance in China's interconnected stock markets are consistent with those in Froot et al. (2001) focusing on the important role of international investors in price discovery on emerging markets. In this way, we show further empirical support to the implication of the theoretical model in Albuquerque et al. (2009).

In our main findings, the information edge, potential round-trip investment and copycat herding all play an important role in the cross-sectional predictability of changes in northbound investors' shareholdings. On the one hand, international institutional investors may be informed about mispricing and earn the abnormal return along with delayed release of public information around the quarterly earnings announcements on the interconnected market. Unlike typical demand pressure patterns in asset pricing, we find announcement effect associated with changes in northbound holdings, suggesting that northbound trading behaviors through the interconnected stock market are more likely to be informed trading. Moreover, investors in A-share markets as well as international markets appear to learn and profit from the cross-sectional predictability over time. Besides, we cannot rule out the prevalence of round-trip investment of mainland funds posing as northbound investors. We would argue that the decay of return predictability after the regulation change on the northbound investor identification show evidence that *some* of domestic investors on the interconnected markets pretend to be northbound participants, hide their true identities and profit from regulation arbitrage driven by the inside information. On the other hand, a subsample of stocks on the Top 10 most actively traded lists, which are more likely affected by imitative herding due to limited attention, show the long-run reversal following an attractive return spread in the subsequent week after formation. It suggests that the flow pressure induced by copycat herding also contributes to the return predictability of changes in shareholdings among investors from the counterparty stock market, at least partially. These results address questions in recent literature about the link between foreign investors' preferences and trading behaviors on the China's mutual market, as well as questions about the relation between the information and asset returns.

Although there is a growing body of research in the Stock Connect Scheme, there are still many open questions. Rather than focus on the difference of pricing efficiency between connected and unconnected stocks before and after the launch of scheme in earlier work on this topic, this study focuses on the implications of information advantage on the pricing of changes in northbound (southbound) shareholdings. Our findings motivate future research that seeks to isolate the role of international investors' informative preferences from the price pressure induced by copycat herding as well as the insider trading driven by regulation arbitrage. A limitation of our study is that in our stock-level tests, we are unable to measure to which degree northbound investors make full use of copycat herding among mainland investors to position themselves and boost their positions' prices. It is also difficult for us to see the complete separation between northbound investors' skills in processing public information and resources of private information. Moreover, one possibility that has not been examined in our paper is whether the positive association between changes in northbound holdings and future stock price that appears to be significant at the daily level might actually reflect intra-day momentum trading by (some) northbound investors. Future research could overcome these limitations and address the concern by incorporating account-level data that clearly trace and identify investors' copycat-, information-, skill- and momentum-motivated trading decisions.

Reference

Agarwal, S., Faircloth, S., Liu, C., & Rhee, S. G. (2009). Why do foreign investors underperform domestic investors in trading activities? Evidence from Indonesia. *Journal of Financial Markets, 12*(1), 32-53.

Aggarwal, R., Erel, I., Ferreira, M., & Matos, P. (2011). Does governance travel around the world? Evidence from institutional investors. *Journal of Financial Economics, 100*(1), 154-181.

Albuquerque, R., Bauer, G. H., & Schneider, M. (2009). Global private information in international equity markets. *Journal of Financial Economics*, *94*(1), 18-46.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross‐section of volatility and expected returns. *The Journal of Finance*, *61*(1), 259-299.

Azémar, C., Desbordes, R., & Mucchielli, J. L. (2007). Do tax sparing agreements contribute to the attraction of FDI in developing countries?. *International Tax and Public Finance, 14*(5), 543-562.

Bailey, W., Mao, C. X., & Sirodom, K. (2007). Investment restrictions and the cross-border flow of information: Some empirical evidence. *Journal of International Money and Finance, 26*(1), 1-25.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies, 21*(2), 785-818.

Barber, B. M., Odean, T., & Zhu, N. (2009). Do retail trades move markets?. *The Review of Financial Studies, 22*(1), 151-186.

Ben-Rephael, A., Da, Z., & Israelsen, R. D. (2017). It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies, 30*(9), 3009-3047.

Brennan, M. J., & Cao, H. H. (1997). International portfolio investment flows. *The Journal of Finance, 52*(5), 1851-1880.

Cai, F., Han, S., Li, D., & Li, Y. (2019). Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics, 131*(1), 139-167.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance, 52*(1), 57-82.

Chen, L. W., Johnson, S. A., Lin, J. C., & Liu, Y. J. (2009). Information, sophistication, and foreign versus domestic investors' performance. *Journal of Banking & Finance, 33*(9), 1636-1651.

Chen, Y., Da, Z., & Huang, D. (2018). Arbitrage trading: The long and the short of it. *The Review of Financial Studies, 32*(4), 1608-1646.

Choe, H., Kho, B. C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics, 54*(2), 227-264.

Choe, H., Kho, B. C., & Stulz, R. M. (2005). Do domestic investors have an edge? The trading experience of foreign investors in Korea. *The Review of Financial Studies, 18*(3), 795-829.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic‐based benchmarks. *The Journal of finance, 52*(3), 1035-1058.

Dvořák, T. (2005). Do domestic investors have an information advantage? Evidence from Indonesia. *The Journal of Finance, 60*(2), 817-839.

Edelen, R. M., Ince, O. S., & Kadlec, G. B. (2016). Institutional investors and stock return anomalies. *Journal of Financial Economics, 119*(3), 472-488.

Edelen, R. M., & Warner, J. B. (2001). Aggregate price effects of institutional trading: a study of mutual fund flow and market returns. *Journal of Financial Economics, 59*(2), 195-220.

Engelberg, J., McLean, R. D., & Pontiff, J. (2018). Anomalies and news. *The Journal of Finance, 73*(5), 1971-2001.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607-636.

Ferreira, M. A., Matos, P., Pereira, J. P., & Pires, P. (2017). Do locals know better? A comparison of the performance of local and foreign institutional investors. *Journal of Banking & Finance*, 82, 151-164.

Froot, K. A., O'connell, P. G., & Seasholes, M. S. (2001). The portfolio flows of international investors. *Journal of financial Economics, 59*(2), 151-193.

Froot, K. A., & Ramadorai, T. (2008). Institutional portfolio flows and international investments. *The Review of Financial Studies, 21*(2), 937-971.

Froot, K., & Teo, M. (2008). Style investing and institutional investors. *Journal of Financial and Quantitative Analysis, 43*(4), 883-906.

Fung, H. G. , & Zhang, Y. G. . (2011). Reported trade figure discrepancy, regulatory arbitrage, and round-tripping: evidence from the china—Hong Kong trade data. *Journal of International Business Studies, 42*(1), 152-176.

Goetzmann, W. N., & Massa, M. (2003). Index funds and stock market growth. *Journal of Business, 76* (2003), 1–28.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of Financial Economics, 55*(1), 43-67.

Grossman, S. J., & Stiglitz, J. E. (1976). Information and competitive price systems. *The American Economic Review, 66*(2), 246-253.

Han, X., & Li, Y. (2017). Can investor sentiment be a momentum time-series predictor? Evidence from China. *Journal of Empirical Finance, 42*, 212-239.

Hau, H. (2001). Location matters: An examination of trading profits. *The Journal of Finance, 56*(5), 1959-1983.

Huang, R. D., & Shiu, C. Y. (2009). Local effects of foreign ownership in an emerging financial market: Evidence from qualified foreign institutional investors in Taiwan. *Financial Management, 38*(3), 567-602.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48*(1), 65-91.

Jia, C., Wang, Y., & Xiong, W. (2017). Market segmentation and differential reactions of local and foreign investors to analyst recommendations. *The Review of Financial Studies, 30*(9), 2972-3008.

Jiao, Y., Massa, M., & Zhang, H. (2016). Short selling meets hedge fund 13F: An anatomy of informed demand. *Journal of Financial Economics, 122*(3), 544-567.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics, 32*(1), 23-43.

Ledyaeva, S., Karhunen, P., Kosonen, R., & Whalley, J. (2015). Offshore foreign direct investment, capital round-tripping, and corruption: Empirical analysis of Russian regions. *Economic Geography*, *91*(3), 305-341.

Liu, C., Wang, S., & Wei, K. C. (2018). Demand Shock, Speculative Beta, and Asset Prices: Evidence from the Shanghai-Hong Kong Stock Connect Program. Working Paper.

Livnat, J., & Mendenhall, R. R. (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of accounting research*, *44*(1), 177-205.

Maffett, M. (2012). Financial reporting opacity and informed trading by international institutional investors. *Journal of Accounting and Economics, 54*(2-3), 201-220.

Mamaysky, H., Spiegel, M., & Zhang, H. (2008). Estimating the dynamics of mutual fund alphas and betas. *The Review of Financial Studies*, 21(1), 233-264.

Richards, A. (2005). Big fish in small ponds: The trading behavior and price impact of foreign investors in Asian emerging equity markets. *Journal of Financial and quantitative Analysis, 40*(1), 1-27.

Seasholes, M. S. (2000). Smart Foreign Traders in Emerging Markets. Harvard Business School, Working Paper.

Shan, C. Y., Tang, Y. J., Wang, Q., & Zhang, C. (2018). The Diversification Benefits and Policy Risks of Accessing China's Stock Market. Working paper.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance, 52*(1), 35-55.

Shukla, R. K., & Van Inwegen, G. B. (1995). Do Locals Perform Better than Foreigners? : An Analysis of UK and US Mutual Fund Managers. *Journal of Economics and Business, 47*(3), 241-254.

Sias, R., Turtle, H. J., & Zykaj, B. (2015). Hedge fund crowds and mispricing. *Management Science, 62*(3), 764-784.

Teo, M. (2009). The geography of hedge funds. *The Review of Financial Studies, 22*(9), 3531-3561.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies, 21*(4), 1455-1508.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance, 54*(2), 581-622.

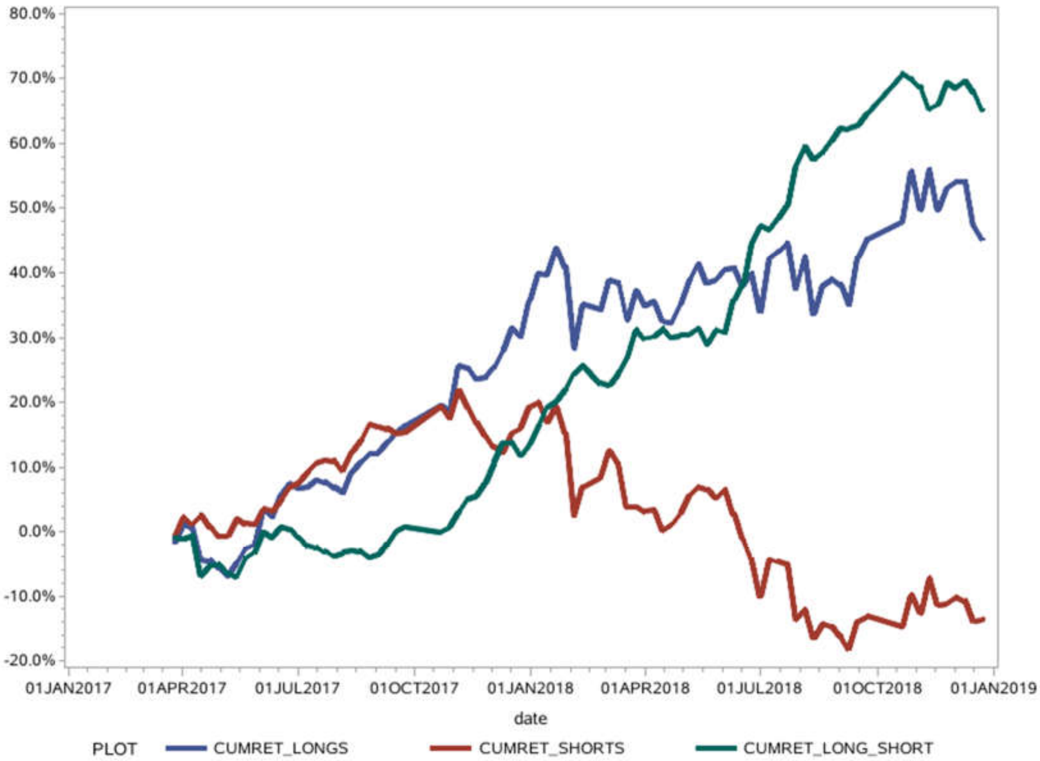
Zhong, Y. L., & Lu, Z. F. (2018). Can the opening of stock market improve the information content of stock price? Empirical evidence from Shanghai-Hong Kong Stock Connect. *Management World, 34*(1), 169-179.

Zhong, K., Sun, C. L., Wang, Y. Z., & Wang, H. C. (2018). Stock market liberalization and idiosyncratic return volatility evidence from "Shanghai–Hong Kong Stock Connect" scheme. *Journal of Financial Research, 7*, 174-192.

Zou, L., Tang, T., & Li, X. (2016). The stock preferences of domestic versus foreign investors: Evidence from Qualified Foreign Institutional Investors (QFIIs) in China. *Journal of Multinational Financial Management, 37*, 12-28.

Figure 1. Cumulative returns for portfolios sorted by HPC

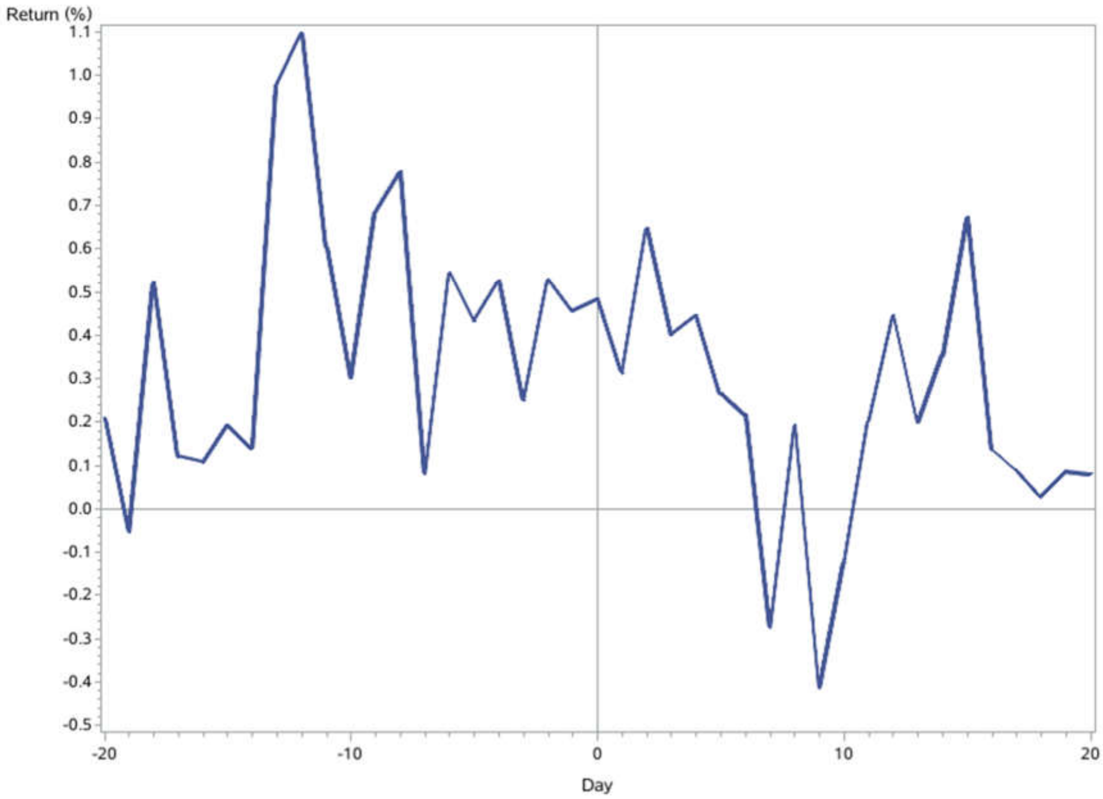
This table plots the cumulative returns for value-weighted portfolios that we form on the change of northbound capital shareholding percent (HPC) from March 2017 to December 2018. At the beginning of each week, eligible stocks in Stock Connect Scheme are sorted into quintile portfolios on the basis of their HPCs and held for one week. Blue line denotes the cumulative returns for long portfolio where the stocks are in the highest HPC quintile. Red line denotes the cumulative returns for short portfolio where the stocks are in the lowest HPC quintile. Green line denotes the hedged portfolio which is constructed by buying long portfolio and selling short portfolio.



Time Series of Cumulative Long/Short/Hedge Strategy Return: Holding 1 week

Figure 2. Daily cross-sectional returns around earnings announcements.

This figure depicts the daily performance of the cross-sectional trading strategy before and after ten days of firm's earnings announcement dates. At the beginning of each trading day, we sort eligible stocks into quintile portfolios on the basis of their previous day's HPCs and hold for one day. "0" in the x-axis denotes the day of earnings announcement, and the value below (above) 0 denotes the trading day before (after) earnings announcement. Y-axis represents the daily high-minus-low returns (in percent).



Daily cross-sectional returns around earnings announcements

Table 1. Summary statistics

This table reports the summary statistics of stock-level and firm-level characteristics from March 2017 to December 2018. Panel A describes the distribution of the main variables in the full sample: the change of shareholding percent (HPC, in percent), denoted as the difference in the ratio of northbound holding to the total shares outstanding between the end of week t and week t-1; level of holding positions among all northbound investors (HP, in percent); the log of market capitalization (Size, in thousand RMB); the book-to-market ratio (BM); the gross profits-to-assets ratio (ROA); stock return volatility (VOL), measured as the standard deviation of daily return over the past 3 months; idiosyncratic volatility (IVOL), computed as the standard deviation of residual from Fama-French three-factor regressions using 3-month daily data; turnover rate (TURN); stock return reversal (REVERSAL), the cumulative return from week t-4 to week t-1; stock return run-up (RUNUP), the cumulative stock return from week t-52 to week t-5. Size, BM, and ROA are quarterly accounting variables; HPC, HP, VOL, IVOL, TURN, RUNUP, and REVERSAL are weekly updated. Summary statistics include mean, median, and the 1th, 25th, 75th, and 99th percentiles. Panel B presents the mean value for main variables in decile portfolios sorted by weekly HPC. Panel C presents the mean value for overseas income in decile portfolios. Detailed definitions about the variables are listed in the Appendix.

Panel A. Summary statistics of full sample							
Variables	Mean	Std. Dev	P1	P25	P50	P75	P99
HPC	0.010	0.421	-0.450	-0.010	0.000	0.030	0.540
HP	0.614	1.698	0.000	0.050	0.170	0.460	8.760
Size	16.703	0.933	15.144	16.058	16.524	17.145	19.724
BM	1.270	2.238	0.103	0.372	0.648	1.259	14.989
ROA	0.035	0.043	-0.032	0.009	0.023	0.049	0.192
VOL	0.023	0.008	0.008	0.017	0.022	0.028	0.046
IVOL	0.018	0.009	0.005	0.012	0.016	0.022	0.046
TURN	7.237	8.165	0.465	2.699	4.778	8.618	40.818
RUNUP	-0.048	0.379	-0.588	-0.277	-0.112	0.100	1.135
REVERSAL	-0.016	0.103	-0.259	-0.076	-0.018	0.039	0.271

Panel B. Decile portfolio sorted by HPC										
Variables	1	2	3	4	5	6	7	8	9	10
HPC	-0.207	-0.043	-0.023	-0.011	0.000	0.007	0.018	0.029	0.061	0.256
HP	1.202	0.489	0.325	0.300	0.206	0.268	0.316	0.421	0.705	1.987
Size	16.594	16.451	16.360	16.355	16.395	16.379	16.403	16.487	16.568	16.750
BM	1.122	1.260	1.213	1.359	1.190	1.312	1.370	1.372	1.427	1.174
ROA	0.043	0.034	0.032	0.031	0.030	0.031	0.030	0.034	0.037	0.049
VOL	0.025	0.023	0.023	0.023	0.022	0.022	0.023	0.022	0.023	0.024
IVOL	0.020	0.018	0.018	0.018	0.017	0.017	0.017	0.018	0.018	0.019
TURN	9.055	7.216	6.819	6.517	7.081	6.475	6.332	6.784	7.310	8.384
RUNUP	0.050	-0.045	-0.102	-0.126	-0.071	-0.113	-0.119	-0.067	-0.019	0.094
REVERSAL	-0.004	-0.016	-0.019	-0.023	-0.019	-0.025	-0.027	-0.019	-0.012	0.000

Panel C. Overseas income of decile portfolio										
HP	0.00	0.02	0.05	0.09	0.14	0.20	0.30	0.46	0.85	3.97
Overseas income/ Total income	0.12	0.11	0.11	0.12	0.12	0.11	0.11	0.10	0.11	0.12
The amount of overseas income	806.84	506.90	718.76	1145.73	1701.16	2352.06	2164.28	2456.06	2926.84	3170.37

Table 2. Univariate portfolio sorts

This table presents average weekly excess returns and alphas (in percent) for value-weighted portfolios calculated over the period March 2017 through December 2018. At the beginning of each week t, eligible stocks in Shanghai/Shenzhen-Hong Kong stock connect scheme are sorted into decile or quintile or bisection portfolios on the basis of their HPCs at week t-1 and held for one week. Panel A displays the weekly excess returns of each portfolio. Panel B calculates the Carhart four-factor adjusted alphas. Panel C adjusts the raw returns based on DGTW method. Panel D reports the excess returns of strategy that skips one week between formation period and holding period. The last row in each panel (High-Low) shows the performance of a long-short portfolio where stocks with HPC in the highest (lowest) quintile are assigned to the long (short) portfolio. Newey and West (1987) three-lag adjusted t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Excess returns

Deciles	Excess return (%)	t-stat
Low	-0.13	(-0.45)
2	-0.17	(-0.65)
3	-0.35	(-1.31)
4	-0.41	(-1.25)
5	-0.29	(-1.03)
6	-0.08	(-0.31)
7	0.00	(0.02)
8	0.08	(0.32)
9	0.22	(0.94)
High	0.48*	(1.83)
High-Low	0.61***	(2.99)

Quintiles	Excess return (%)	t-stat
Low	-0.15	(-0.54)
2	-0.31	(-1.23)
3	-0.17	(-0.74)
4	0.05	(0.21)
High	0.35	(1.41)
High-Low	0.50***	(3.11)

Halves	Excess return (%)	t-stat
Low	-0.18	(-0.75)
High	0.17	(0.75)
High-Low	0.35***	(3.10)

	Panel B: Carhart 4 factor alphas		Panel C: DGTW adjusted return		Panel D: One-week skip	
	Alpha (%)	t-stat	Excess return (%)	t-stat	Excess return (%)	t-stat
Low	0.06	(0.52)	-0.12	(-0.41)	-0.21	(-0.77)
2	0.02	(0.23)	-0.17	(-0.68)	-0.10	(-0.42)
3	-0.21*	(-1.83)	-0.31	(-1.17)	-0.13	(-0.53)
4	-0.06	(-0.30)	-0.40	(-1.20)	-0.25	(-0.86)
5	-0.11	(-0.89)	-0.27	(-0.89)	-0.41	(-1.64)
6	0.21*	(1.71)	0.00	(0.01)	-0.57*	(-1.90)
7	0.28*	(1.77)	-0.03	(-0.11)	-0.11	(-0.39)
8	0.32***	(2.97)	0.08	(0.32)	-0.13	(-0.55)
9	0.43***	(5.15)	0.24	(0.99)	0.12	(0.46)
High	0.66***	(5.65)	0.48*	(1.83)	0.15	(0.56)
High-Low	0.59***	(2.90)	0.60***	(2.98)	0.36***	(2.61)

Table 3. Fama-MacBeth regression

This table reports the results of second stage Fama-MacBeth regression. The dependent variable for all the models is the returns of long-short portfolio formed by sorting weekly HPC. In Model (1), only lagged HPC is included as the independent variable. In Model (2), firm-level and stock-level characteristics are added as control variables, including SIZE, BM, ROA, IVOL, TURN, MSCI, past one-week stock return (PastRet (1w)), past one-month stock return (REVERSAL), past one- to three-month stock return (PastRet (1m-3m)), and past twelve-month stock return (RUNUP). In Model (3), contemporaneous HPC is taken into account to control for the effect of capital flow pressure. All regressions are run at a weekly frequency from March 2017 to December 2018. Newey-West three-lag adjusted t-statistics are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
HPC(t-1)	1.12***	0.86***	0.69***
	(6.03)	(6.55)	(4.95)
HPC(t)			1.01***
			(3.85)
Size		0.02	0.02
		(0.46)	(0.44)
BM		0.02	0.02
		(1.36)	(1.41)
ROA		0.44	0.39
		(0.28)	(0.24)
PastRet(1w)		-2.17	-2.19
		(-1.56)	(-1.57)
REVERSAL		0.88	0.83
		(1.04)	(0.98)
PastRet(1m-3m)		0.65	0.63
		(1.38)	(1.35)
RUNUP		0.11	0.10
		(0.80)	(0.73)
IVOL		-3.29	-3.26
		(-0.64)	(-0.64)
TURN		-0.04***	-0.04***
		(-5.94)	(-5.86)
MSCI		0.24***	0.24***
		(3.88)	(3.93)

Table 4. Variation of cross-sectional predictability across market and over time

This table reports the variation of cross-sectional predictability across market and over time. Portfolio sorting is the same as the process in Panel A of Table 2, but in different sub-samples. Panel A examines the decile portfolios and long-short portfolio returns using eligible stocks listed in Shanghai and Shenzhen, respectively. Panel B examine the weekly portfolio returns in two sub-periods. We divided the full sample equally into two sub-periods. The first period is March 2017 to January 2018, and the second period is February 2018 to December 2018. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Excess return (%)	t-stat	Excess return (%)	t-stat
Panel A. Stock exchange				
	Shanghai		Shenzhen	
Low	-0.16	(-0.55)	-0.01	(-0.02)
2	-0.12	(-0.45)	-0.21	(-0.70)
3	-0.41	(-1.47)	-0.26	(-0.85)
4	-0.45	(-1.49)	-0.39	(-0.91)
5	-0.27	(-0.90)	-0.34	(-1.13)
6	0.22	(0.86)	-0.50	(-1.33)
7	0.01	(0.04)	-0.08	(-0.24)
8	0.15	(0.60)	-0.05	(-0.18)
9	0.39	(1.57)	-0.04	(-0.15)
High	0.41	(1.62)	0.50*	(1.68)
High-Low	0.56***	(2.61)	0.51*	(1.96)
Panel B. Sub-periods				
	First half		Second half	
Low	0.34	(1.31)	-0.59	(-1.21)
2	0.30	(1.17)	-0.62	(-1.47)
3	0.10	(0.36)	-0.78*	(-1.71)
4	-0.50	(-1.35)	-0.36	(-0.82)
5	0.15	(0.56)	-0.62	(-1.50)
6	-0.14	(-0.37)	-0.04	(-0.14)
7	0.24	(0.64)	-0.23	(-0.61)
8	0.14	(0.45)	0.01	(0.04)
9	0.58**	(2.35)	-0.13	(-0.34)
High	0.84***	(2.66)	0.12	(0.31)
High-Low	0.51*	(1.70)	0.71***	(2.61)

Table 5. Cross-sectional return predictability in different formation and holding weeks

This table reports the accumulative returns (in percent) for long-short portfolios employing different length of formation weeks (F) and holding weeks (H). In Panel A, portfolios are constructed as follows: at the beginning of each week t, the eligible stocks are sorted into quintiles on the basis of F-week lagged HPC. Then we construct the long-short portfolio by buying stocks with HPC in the highest quintile, and selling stocks with HPC in the lowest quintile, and hold for H weeks. Average cumulative return is calculated by averaging the H-week cumulative returns generated at each week. In Panel B, we employ Jegadeesh and Titman (1993) method to construct portfolios. At the beginning of each week t, the eligible stocks on the interconnected market are ranked in ascending order on the basis of their HPC in the past F weeks, and sorted into five quintile portfolios. In each week t, we buy the stocks with HPC in the highest quintile (denoted as "Long") and sell the stocks with HPC in the lowest quintile (denoted as "Short"). The position is held for H weeks. In addition, we close out the position initiated in week t-F. Under this trading strategy, we revise the weights on 1/F of the stocks in the entire portfolio in any given week and carry over the rest from the previous week. The values of F and H are set to be 1, 2, and 4, respectively. Sample period is March 2017 to December 2018. Newey-West adjusted t-statistics are given below the portfolio returns in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Cross-sectional returns in the long run

	H							
F	1	2	3	4	5	6	7	8
1	0.50***	0.74***	1.11***	1.25***	1.32***	1.38***	1.28***	1.58***
	(3.31)	(4.01)	(4.90)	(4.54)	(4.57)	(4.00)	(3.28)	(3.81)
2	0.44***	0.86***	1.19***	1.34***	1.49***	1.46***	1.62***	1.93***
	(3.20)	(4.82)	(5.47)	(4.86)	(4.71)	(3.93)	(4.01)	(4.36)
3	0.60***	0.96***	1.30***	1.52***	1.53***	1.55***	1.78***	2.05***
	(4.20)	(5.47)	(5.56)	(4.88)	(4.55)	(3.97)	(4.10)	(4.36)
4	0.52***	0.92***	1.30***	1.38***	1.45***	1.65***	1.83***	2.11***
	(3.67)	(5.22)	(5.73)	(4.77)	(4.64)	(4.35)	(4.32)	(4.59)

Panel B. Cross-sectional returns based on Jegadeesh and Titman (1993) method

	F = 1			F = 2			F = 4		
H	1	2	4	1	2	4	1	2	4
Long	0.48	0.28	0.21	0.32	0.24	0.20	0.33	0.23	0.18
	(1.58)	(0.92)	(0.70)	(1.03)	(0.79)	(0.64)	(1.06)	(0.71)	(0.55)
Short	-0.13	-0.19	-0.12	-0.16	-0.23	-0.15	-0.17	-0.19	-0.12
	(-0.39)	(-0.59)	(-0.40)	(-0.51)	(-0.74)	(-0.49)	(-0.55)	(-0.59)	(-0.41)
Long-Short	0.61***	0.47***	0.34***	0.47***	0.48***	0.35***	0.49***	0.42***	0.30**
	(3.32)	(3.98)	(4.07)	(2.91)	(4.06)	(3.51)	(2.99)	(2.77)	(2.15)

Table 6. The determinants of HP and HPC

Panel A and Panel B in this table present the level of northbound capital shareholding (HP), and the potential determinants of the change of northbound capital shareholding percent (HPC), respectively. Sample period is March 2017 to December 2018. Independent variables include Size, the log of market capitalization (in thousand RMB) at the end of last Friday; BM, the latest book-to-market ratio calculated at least 3 month ago; ROA, the latest gross profits-a-assets ratio calculated at least 3 month ago; SOE, a dummy variable with 1 denoting that the firm is state-owned, and 0 denoting non-state-owned; VOL, the standard deviation of daily return over the past 3 months; IVOL, idiosyncratic volatility which is calculated as the standard deviation of return residual from Fama-French three-factor regressions using past 3-month daily data; TURN, the turnover rate in the past week; REVERSAL, the cumulative return from week t-4 to week t-1; RUNUP, return momentum which is the cumulative stock return from week t-52 to week t-5; MSCI, a dummy with 1 indicating the firm is listed in MSCI China index, and 0 indicating the opposite; InstHold, the ratio of shares held by institutional investors to the number of A shares outstanding; AnalyNum, the number of analysts covered the firm during past year. There is no fixed effect in Model (1); Model (2) has industry fixed; Model (3) has year-month fixed effect; Model (4)-Model (7) have both industry and year-month fixed effect. Standard errors are clustered at industry level. *, ** and *** represent statistical significance at the 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. The determinants of HP							
Size	0.491***	0.530***	0.523***	0.564***	0.552***	0.462***	0.452***
	(67.65)	(72.98)	(71.81)	(5.61)	(5.50)	(4.28)	(4.16)
BM	-0.157***	-0.143***	-0.185***	-0.182***	-0.183***	-0.184***	-0.185***
	(-32.32)	(-25.45)	(-37.52)	(-2.83)	(-2.87)	(-2.71)	(-2.74)
ROA	3.143***	2.652***	3.570***	3.053***	3.052***	2.278**	2.276**
	(25.38)	(21.89)	(26.02)	(3.06)	(3.10)	(2.00)	(2.01)
SOE	0.054***	0.075***	0.063***	0.090	0.068	0.097	0.077
	(5.01)	(6.47)	(5.90)	(1.29)	(0.90)	(1.18)	(0.89)
VOL	19.747***	22.114***	-2.001*	-0.630	-1.029	-6.339	-6.680
	(20.98)	(24.15)	(-1.87)	(-0.17)	(-0.28)	(-1.51)	(-1.58)
IVOL	-0.627	-1.430*	3.050***	2.196	1.711	2.084	1.690
	(-0.74)	(-1.76)	(3.54)	(1.43)	(1.03)	(1.18)	(0.91)
TURN	-2.295***	-1.882***	-1.364***	-0.952***	-0.746**	-0.628**	-0.451
	(-28.01)	(-23.66)	(-15.98)	(-3.88)	(-2.60)	(-2.02)	(-1.31)
REVERSAL	0.306***	0.151***	0.292***	0.153	0.133	0.175	0.159
	(6.12)	(3.15)	(5.56)	(1.18)	(0.99)	(1.27)	(1.11)
RUNUP	0.262***	0.160***	0.422***	0.327***	0.325***	0.365***	0.362***
	(17.50)	(10.87)	(27.64)	(3.37)	(3.32)	(3.53)	(3.47)
MSCI	1.062***	1.004***	0.698***	0.640***	0.638***	0.552***	0.551***
	(42.56)	(42.01)	(26.66)	(3.22)	(3.22)	(2.84)	(2.84)
InstHold					0.169		0.153
					(1.51)		(1.36)
AnalyNum						0.019***	0.019***
						(4.49)	(4.45)

(Continued on the next page)

Table 6 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. The determinants of HP			
Industry FX	No	Yes	No	Yes	Yes	Yes	Yes
Month FX	No	No	Yes	Yes	Yes	Yes	Yes
#observations	107,770	107,770	107,770	107,770	107,400	98,710	98,493
R^2	0.145	0.224	0.167	0.245	0.246	0.260	0.260
				Panel B. The determinants of HPC			
Size	0.002	0.002	0.001	0.002**	0.002*	0.001	0.001
	(1.03)	(1.23)	(0.81)	(2.12)	(1.80)	(0.63)	(0.45)
BM	0.001	0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.93)	(1.01)	(-0.60)	(-1.08)	(-1.12)	(-1.01)	(-1.04)
ROA	0.176***	0.178***	0.113***	0.113***	0.113***	0.108***	0.107***
	(6.13)	(6.02)	(3.53)	(5.99)	(6.01)	(5.27)	(5.26)
SOE	-0.000	0.000	-0.000	0.000	0.000	0.001	0.000
	(-0.08)	(0.16)	(-0.11)	(0.54)	(0.04)	(0.70)	(0.23)
VOL	0.642***	0.632***	-0.059	-0.100	-0.104	-0.110	-0.116
	(2.94)	(2.83)	(-0.23)	(-0.75)	(-0.78)	(-0.71)	(-0.75)
IVOL	-0.538***	-0.553***	0.089	0.081	0.077	0.085	0.079
	(-2.73)	(-2.79)	(0.44)	(0.58)	(0.55)	(0.56)	(0.52)
TURN	-0.020	-0.015	-0.047**	-0.043***	-0.041***	-0.048***	-0.044***
	(-1.06)	(-0.78)	(-2.37)	(-4.02)	(-3.48)	(-3.56)	(-3.13)
REVERSAL	0.023**	0.022*	0.056***	0.055***	0.055***	0.062***	0.061***
	(2.00)	(1.85)	(4.61)	(4.35)	(4.34)	(4.56)	(4.52)
RUNUP	0.004	0.003	0.007**	0.006***	0.006***	0.007***	0.007***
	(1.10)	(0.76)	(1.98)	(4.25)	(4.19)	(4.01)	(3.97)
MSCI	0.009	0.009	0.007	0.007*	0.006*	0.006*	0.006*
	(1.60)	(1.56)	(1.09)	(1.98)	(1.98)	(1.88)	(1.87)
InstHold					0.003**		0.003**
					(2.14)		(2.00)
AnalyNum						0.000	0.000
						(1.32)	(1.34)
Industry FX	No	Yes	No	Yes	Yes	Yes	Yes
Month FX	No	No	Yes	Yes	Yes	Yes	Yes
# observations	107,770	107,770	107,770	107,770	107,400	98,710	98,493
R^2	0.001	0.001	0.017	0.017	0.017	0.018	0.018

Table 7. Cross-sectional returns around information release

This table reports the cumulative returns (in percent) for portfolios sorted by the change of northbound capital shareholding percent (HPC) around quarterly earnings announcements. We divide previous week's HPC into five quintiles three days before the announcement of quarterly earnings. Holding week varies from one week ([-2,2] around the earnings announcement) to eight weeks to be comparable with the results in Table 5. Cumulative return calculation is the same as that in Table 5. Sample period is March 2017 to December 2018. Newey-West adjusted t-statistics are given below the portfolio returns in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	H							
F	1	2	3	4	5	6	7	8
Low	-0.45*	-0.74**	-1.11***	-1.14***	-1.27***	-1.42**	-1.51**	-1.72**
	(-1.74)	(-2.10)	(-2.70)	(-2.58)	(-2.62)	(-2.50)	(-2.30)	(-2.44)
2	-0.38	-0.71**	-1.19***	-1.47***	-1.57***	-1.97***	-2.37***	-2.75***
	(-1.53)	(-2.09)	(-3.08)	(-3.41)	(-3.17)	(-3.44)	(-3.86)	(-4.42)
3	-0.30	-0.60**	-0.92**	-1.10***	-1.29***	-1.51***	-1.69***	-1.72***
	(-1.36)	(-1.98)	(-2.57)	(-2.73)	(-2.97)	(-3.35)	(-3.45)	(-3.28)
4	-0.25	-0.49	-0.69*	-0.91*	-0.99**	-1.20**	-1.28**	-1.26**
	(-1.03)	(-1.46)	(-1.74)	(-1.94)	(-2.06)	(-2.22)	(-2.26)	(-2.16)
High	0.07	0.09	0.10	0.23	0.26	0.18	0.36	0.59
	(0.28)	(0.25)	(0.24)	(0.46)	(0.51)	(0.32)	(0.59)	(0.86)
High-Low	0.52***	0.83***	1.21***	1.36***	1.53***	1.60***	1.88***	2.31***
	(3.30)	(3.93)	(4.85)	(4.39)	(4.51)	(4.06)	(4.44)	(5.10)

Table 8. HPCs forecast CARs and SUEs around QEAs

This table reports the predictability of HPC on earnings surprises and abnormal returns around earnings announcements. Following Livnat and Mendenhall (2006), standard earnings surprises are defined as: $SUE_{i,t} = \frac{X_{i,t}-X_{i,t-4}}{P_{i,t}}$, where $X_{i,t}$ is earnings per share for firm i in quarter t. Five-day buy-and-hold abnormal returns is measured based on the market model, where the market benchmark is defined as the value-weighted portfolio of all A-share stocks listed on stock exchanges. Estimation window is required to be one year [-376, -11] for each stock, with minimum observations of 90 trading days. HPC is the difference of holding ratio between t-1 and t-6, where t is first day of event window. Control variables include Size, BM, ROA, SOE, VOL, IVOL, TURN, REVERSAL, RUNUP, MSCI, InstHold, and AnalyNum. Panel A reports the full sample prediction results. Panel B compares the predictability of HPC between subsamples where firms' overseas income is above and below the sample median. Industry and year-month fixed effect are included. Standard errors are clustered at industry level. Sample period is March 2017 to December 2018.

	SUE				CAR[-2,2]			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
				Panel A. Full sample				
HPC	0.0003**	0.0003**	0.0003**	0.0003**	0.0309**	0.0305**	0.0304**	0.0301**
	(2.27)	(2.26)	(2.24)	(2.22)	(2.46)	(2.43)	(2.48)	(2.46)
Size	-0.0004	-0.0004	0.0002	0.0001	-0.0019**	-0.0017**	-0.0023***	-0.0023**
	(-1.20)	(-1.35)	(0.44)	(0.21)	(-2.56)	(-2.43)	(-2.70)	(-2.65)
BM	0.0010***	0.0010***	0.0011***	0.0011***	0.0022***	0.0022***	0.0023***	0.0023***
	(3.45)	(3.43)	(3.35)	(3.32)	(4.47)	(4.48)	(4.65)	(4.66)
ROA	0.0213***	0.0213***	0.0248***	0.0247***	0.0342**	0.0329**	0.0356**	0.0347**
	(3.39)	(3.40)	(3.79)	(3.77)	(2.49)	(2.40)	(2.18)	(2.13)
SOE	0.0006	0.0004	0.0006	0.0005	-0.0017	-0.0017	-0.0013	-0.0014
	(1.12)	(0.89)	(1.42)	(1.09)	(-1.35)	(-1.30)	(-0.99)	(-1.02)
VOL	-0.0641	-0.0657	-0.0503	-0.0525	0.2628**	0.2597**	0.2789**	0.2794**
	(-1.19)	(-1.22)	(-0.84)	(-0.87)	(2.59)	(2.47)	(2.41)	(2.36)
IVOL	0.0032	0.0036	-0.0028	-0.0021	-0.2333***	-0.2324***	-0.2303***	-0.2295***
	(0.14)	(0.16)	(-0.11)	(-0.08)	(-3.11)	(-3.02)	(-2.72)	(-2.71)
TURN	0.0024	0.0030	0.0014	0.0022	-0.0285***	-0.0276***	-0.0285***	-0.0284***
	(0.73)	(0.92)	(0.39)	(0.59)	(-3.33)	(-3.01)	(-3.16)	(-2.98)
REVERSAL	0.0061***	0.0059***	0.0069***	0.0067***	-0.0033	-0.0039	-0.0007	-0.0010
	(3.13)	(2.95)	(3.49)	(3.25)	(-0.51)	(-0.61)	(-0.10)	(-0.15)
RUNUP	0.0091***	0.0091***	0.0089***	0.0089***	-0.0091***	-0.0090***	-0.0098***	-0.0098***
	(11.47)	(11.30)	(10.62)	(10.58)	(-5.41)	(-5.42)	(-4.49)	(-4.49)
MSCI	-0.0000	-0.0000	-0.0001	-0.0001	0.0013	0.0012	0.0014	0.0014
	(-0.07)	(-0.06)	(-0.18)	(-0.17)	(0.62)	(0.55)	(0.64)	(0.61)
InstHold		0.0000		0.0000		-0.0000		-0.0000
		(1.34)		(1.51)		(-0.67)		(-0.16)
AnalyNum			-0.0001***	-0.0001***			0.0000	0.0000
			(-3.94)	(-3.95)			(1.16)	(1.14)

(Continued on the next page)

Table 8 (Continued)

Industry FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FX	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	6,954	6,948	6,464	6,459	7,259	7,242	6,689	6,681
R-squared	0.172	0.172	0.186	0.186	0.061	0.060	0.059	0.058
Panel B. Comparison in subsamples divided by the median of firms overseas income								
HPC (Overseas	0.0004**	0.0004**	0.0004**	0.0004**	0.0471***	0.0464***	0.0440**	0.0430**
Income>Median)	(2.47)	(2.60)	(2.26)	(2.49)	(2.90)	(2.86)	(2.60)	(2.54)
HPC (Overseas	-0.0001	-0.0002	-0.0001	-0.0001	0.0005	0.0012	-0.0045	-0.0048
Income<Median)	(-0.60)	(-0.68)	(-0.46)	(-0.53)	(0.02)	(0.05)	(-0.22)	(-0.24)
Diff	0.0005*	0.0006*	0.001	0.0005*	0.0466*	0.0452*	0.0485**	0.0478**
P-value	0.08	0.06	0.12	0.08	0.08	0.09	0.04	0.04

Table 9. Double sort portfolio

This table reports average weekly excess returns (in percent) for 2×5 value-weighted portfolios conditional on different firm characteristics over the period March 2017 through December 2018. At the beginning of each week, we form sequential double-sort portfolios based on lagged rank characteristics and hold for one week. The first rank variable in Panel A, Panel B, and Panel C is the level of northbound capital holding (HP), A-H cross list, and overseas income, respectively. The second rank variable in each panel is the change of northbound capital shareholding percent (HPC). The last column in each panel (High-Low) shows return to a long-short portfolio where firms with HPC in the highest (lowest) are assigned to the long (short) portfolio. The last row in each panel shows the average return of quintile portfolios in each column. Newey-West adjusted t-statistics are given below the portfolio returns in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A Conditional on HP						
	HPC					
HP	Low	2	3	4	High	High-Low
High	-0.09	-0.17	-0.03	0.16	0.38	0.56***
	(-0.31)	(-0.58)	(-0.11)	(0.59)	(1.28)	(4.02)
Low	-0.44	-0.50*	-0.32	-0.24	-0.01	0.44***
	(-1.32)	(-1.88)	(-1.29)	(-0.76)	(-0.03)	(2.93)
High-Low	0.35	0.33	0.30*	0.39*	0.46**	0.09
	(1.64)	(1.52)	(1.79)	(1.86)	(2.11)	(0.53)
Panel B. Conditional on A-H cross-listing						
	HPC					
A-H	Low	2	3	4	High	High-Low
Cross-listing	0.69**	0.33	-0.07	-0.28	-0.13	0.81***
	(2.60)	(1.28)	(-0.23)	(-1.03)	(-0.36)	(3.33)
Non-cross-listing	0.28	-0.06	-0.27	-0.29	-0.15	0.43***
	(1.14)	(-0.25)	(-1.04)	(-1.02)	(-0.60)	(2.99)
(Cross-listing)-(Non-cross-listing)	-0.35**	-0.40	-0.20	-0.01	-0.03	0.30
	(-2.03)	(-1.49)	(-0.71)	(-0.02)	(-0.12)	(1.39)
Panel C. Conditional on overseas income						
	HPC					
Overseas income	Low	2	3	4	High	High-Low
High	-0.19	-0.40	0.03	0.27	0.30	0.49**
	(-0.54)	(-1.41)	(0.15)	(0.92)	(0.91)	(2.25)
Low	0.01	-0.37	-0.35	-0.24	-0.03	-0.04
	(0.03)	(-1.04)	(-1.14)	(-0.74)	(-0.10)	(-0.24)
High-Low	-0.20	-0.03	0.38	0.52**	0.33	0.53**
	(-0.91)	(-0.10)	(1.58)	(2.38)	(1.60)	(2.20)

Table 10. Cross-sectional return predictability in Southbound capital

This table reports the weekly returns (in percent) of H-share stock portfolios sorted by their share changes held by southbound investors from China Mainland. Individual stocks on the interconnected markets are sorted into decile portfolios. In Panel A, both the formation period and holding period are one week. We examine the portfolio performance for the full sample and two sub-samples: firms connected with Mainland, and firms not connected with Mainland. In Panel B, we examine the long-run portfolio performance. Formation period is one week. Holding period varies from one to eight weeks. Sample period is March 2017 to December 2018. Newey-West adjusted t-statistics are given in parentheses. *, ** and *** represent statistical significance at the 10%, 5% and 1%, respectively.

Panel A. Baseline performance

	All firms		Mainland firms		Non-Mainland firms	
Stock portfolios	Excess return (%)	t-stat	Excess return (%)	t-stat	Excess return (%)	t-stat
Low	-0.19	(-0.63)	-0.22	(-0.65)	-0.07	(-0.24)
2	0.11	(0.44)	0.13	(0.44)	0.06	(0.28)
3	0.14	(0.64)	0.15	(0.57)	0.06	(0.30)
4	0.35	(1.19)	0.40	(1.21)	0.36	(1.47)
High	0.45	(1.28)	0.59	(1.67)	0.41	(0.94)
High-Low	0.64***	(3.85)	0.72***	(4.59)	0.48	(1.12)

Panel B. Long-run performance

Holding weeks	1	2	3	4	5	6	7	8
Low	-0.19	-0.16	-0.10	-0.04	-0.14	-0.11	-0.06	-0.04
2	0.11	0.14	0.14	0.17	0.17	0.10	-0.09	-0.07
3	0.14	0.28	0.53	0.63	0.75	0.93	1.22	1.30
4	0.35	0.55	0.83	1.16	1.57	1.67	1.87	2.17
High	0.45	0.65	0.89	1.01	1.20	1.15	1.38	1.69
High-Low	0.64***	0.81**	0.99***	1.05**	1.34***	1.25**	1.44***	1.73**
	(3.85)	(3.69)	(3.73)	(4.08)	(4.45)	(3.69)	(3.74)	(3.88)

Table 11. Cross-sectional returns before and after regulation change

This table compares the cross-sectional return predictability of northbound and southbound HPC before and after the regulation change. On August 24, 2018, HKEX announced to construct Northbound investor identification model for northbound trading in Stock Connect Scheme. Thus, the period before the regulation change is from March 2017 to August 24, 2018, and the period after the regulation change is from September 2018 to the present. Panel A reports the weekly portfolio returns of northbound HPC and Panel B reports the results of southbound HPC. Newey-West adjusted t-statistics are given in parentheses. *, ** and *** represent statistical significance at the 10%, 5% and 1%, respectively.

	Excess return (%)	t-stat	Excess return (%)	t-stat
	Before		After	
Panel A. Sorted by northbound HPC				
Low	-0.15	(-0.47)	0.89*	(1.72)
2	-0.21	(-0.75)	0.70	(1.34)
3	-0.37	(-1.40)	0.82	(1.54)
4	-0.51	(-1.46)	0.65	(1.53)
5	-0.26	(-0.83)	0.57	(1.48)
6	-0.14	(-0.50)	0.76*	(1.82)
7	-0.03	(-0.10)	0.94*	(1.74)
8	0.04	(0.15)	1.20**	(2.14)
9	0.24	(0.96)	1.15**	(2.40)
High	0.53*	(1.98)	1.13**	(2.29)
High-Low	0.68***	(3.14)	0.24	(0.94)
Panel B. Sorted by southbound HPC				
Low	-0.32	(-1.08)	-0.07	(-0.13)
2	0.02	(0.08)	0.09	(0.24)
3	0.03	(0.11)	-0.08	(-0.25)
4	0.15	(0.66)	1.34	(1.51)
5	0.08	(0.33)	-0.39	(-1.60)
6	0.03	(0.12)	1.11	(1.61)
7	0.16	(0.53)	0.27	(0.82)
8	0.10	(0.30)	0.05	(0.13)
9	0.46	(1.61)	0.19	(0.46)
High	0.29	(0.77)	0.60	(1.16)
High-Low	0.60***	(2.76)	0.67***	(2.97)

Table 12. Copycat herding

This table reports the portfolio performance based on daily list of Top 10 most actively traded stocks. Panel A and Panel B examine the value-weighted portfolios formed on weekly herding signal in a two-week rolling window. We use the subsample of A shares which are on the daily list of ten most actively traded stocks to construct the quintile portfolios. Following Cai et al. (2019), Lakonishok, Shleifer and Vishny (1992), and Wermers (1999), the volume-based herding measure is defined as:

$$VBHD_{i,t} = \frac{purchases_{i.t} - sales_{i,t}}{purchases_{i,t} + sales_{i,t}}$$

where $purchases_{i.t}$ and $sales_{i,t}$ denote the buying and selling of stock i of northbound investors within week t, respectively. Panel A presents the cumulative returns for quintile portfolios and long-short portfolio, where holding period varies from one week to eight weeks. Panel B presents the average cumulative changes in shareholdings among northbound investors for each portfolio formed by weekly herding signal in Panel A. Panel C and Panel D examine the value-weighted portfolios formed on daily herding measure using A shares which appear on the list of Top 10 daily trading volume at least once. Panel C reports the daily excess returns for the quintile portfolios on the next *n*th trading day. Panel D reports the average stocks ranks within each portfolio on the next *n*th trading day. Sample period is from March 2017 through December 2018. Newey-West adjusted t-statistics are given below the portfolio returns in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Cumulative weekly returns								
	1	2	3	4	5	6	7	8
Low	0.01	0.26	0.44	0.75	0.91	1.02	1.45	1.59
2	0.25	0.42	0.77	1.17	1.10	1.18	1.24	1.42
3	0.31	0.41	0.59	0.89	1.19	1.35	1.47	1.87
4	0.65	0.84	0.94	0.97	1.24	1.64	1.82	2.13
High	0.68	1.05	1.32	1.52	1.75	1.62	1.63	1.61
High-Low	0.67**	0.79**	0.89**	0.77	0.83	0.60	0.18	0.02
	(2.40)	(2.32)	(2.13)	(1.61)	(1.57)	(1.08)	(0.29)	(0.03)
Panel B: Cumulative changes in shareholdings among northbound investors								
	1	2	3	4	5	6	7	8
Low	0.17	-0.04	-0.02	-0.10	0.03	0.25	0.47	0.67
2	-0.12	0.12	0.18	0.26	0.27	0.28	0.66	0.51
3	0.19	-0.11	-0.05	0.22	0.04	0.26	0.32	0.61
4	0.49	0.77	0.98	1.10	1.15	1.02	1.23	1.26
High	0.61	0.69	0.63	0.68	0.76	0.86	1.15	1.44
High-Low	0.43	0.73**	0.65*	0.79*	0.73	0.61	0.68	0.77
	(1.39)	(2.19)	(1.69)	(1.78)	(1.57)	(1.14)	(1.18)	(1.23)

Panel C. Excess daily returns				
	1	2	3	4
Low	-0.22***	-0.02	-0.07	-0.02
	(-4.32)	(-0.47)	(-1.42)	(-0.45)
2	-0.13***	-0.10**	-0.04	-0.06
	(-2.75)	(-2.13)	(-0.76)	(-1.30)

(Continued on the next page)

Table 12 (Continued)

3	0.04	0.10**	0.08*	0.00
	(0.80)	(2.10)	(1.75)	(-0.06)
4	0.20***	0.04	0.10**	0.09*
	(4.43)	(0.92)	(2.10)	(1.91)
High	0.35***	0.23***	0.16***	0.17***
	(7.78)	(4.84)	(3.35)	(3.64)

Panel D. Average daily stock ranks

	1	2	3	4
Low	1.16	1.37	1.52	1.55
2	1.60	1.68	1.73	1.76
3	1.93	1.91	1.87	1.89
4	2.27	2.14	2.06	2.05
High	2.90	2.77	2.60	2.58

Table 13. Time-series prediction

This table reports the time-series prediction at weekly frequency from November 2014 to December 2018. We use the lagged predictor labelled in column to predict the excess returns of market index labelled in row, respectively. Predictors include net inflows of north bound capital (buy amount minus sell amount), net inflows of north bound capital in SH-HK connect, net inflows of north bound capital in SZ-HK connect. Market index include value weighted portfolio of all A shares (AllAShares), value weighted portfolio of A shares in Shanghai stock market (SHZA), value weighted portfolio of A shares in Shenzhen stock market (SZAZ). In-sample prediction utilizes the full sample data from November 2014 to December 2018. For out-of-sample prediction, forecasting model is estimated using a recursive window starting from November 2014. Benchmark is the historical mean model. We examine three sub-periods for out-of-sample test: January 2016 to December 2018, January 2017 to December 2018, January 2018 to December 2018. Panel A presents the R^2 for in-sample prediction. Panel B and Panel C present the R_{OS}^2 and annualized certainty equivalent return for out-of-sample prediction.

Panel A. In-sample prediction

	AllAShares	SHAZ	SZAZ
	R^2	R^2	R^2
NetAmt_North	2.16%	0.06%	3.39%
NetAmt_SH	1.75%	-0.27%	2.87%
NetAmt_SZ	2.54%	2.56%	2.42%

Panel B. Out-of-sample R_{OS}^2

	2016.1.1-2018.12.31			2017.1.1-2018.12.31			2018.1.1-2018.12.31		
	AllAShares	SHZA	SZAZ	AllAShares	SHZA	SZAZ	AllAShares	SHZA	SZAZ
NetAmt_North	3.48%	1.11%	3.38%	4.12%	2.01%	3.75%	6.37%	2.30%	6.86%
NetAmt_SH	2.36%	0.20%	2.22%	3.53%	0.54%	3.34%	5.06%	0.65%	5.81%
NetAmt_SZ	0.41%	-0.15%	0.92%	0.41%	-0.15%	0.92%	1.56%	1.19%	1.75%

Panel C. Annualized certainty equivalent return

	2016.1.1-2018.12.31			2017.1.1-2018.12.31			2018.1.1-2018.12.31		
	AllAShares	SHZA	SZAZ	AllAShares	SHZA	SZAZ	AllAShares	SHZA	SZAZ
NetAmt_North	19.09%	10.58%	13.32%	24.31%	15.81%	15.03%	42.81%	30.59%	21.44%
NetAmt_SH	21.70%	8.80%	15.83%	30.61%	13.30%	21.63%	51.46%	25.13%	29.85%
NetAmt_SZ	2.44%	-4.22%	-3.30%	3.64%	-2.07%	-1.44%	-2.31%	-2.48%	-23.05%

Table 14. Time-series trading strategy

This table reports the performance of time-series trading strategy. The design of the strategy is: At the end of each week, the investor will take a long position if the predicted market return is positive. Otherwise the investor will liquidate the market portfolio and use the proceeds to invest in the risk-free asset. Holding period varies from one week to eight weeks. We employ the methodology of Jegadeesh and Titman (1993) with active portfolios to derive the single time series of the monthly returns for all holding periods larger than one week. We only consider one market index and one predictor in this table. Market return is value-weighted A shares portfolio. Predictor is the net inflows of total northbound capital through Shanghai/Shenzhen-Hong Kong stock connect. Forecasting model is estimated using a recursive window starting from November 2014. Out-of-sample evaluation period extends from January 2016 to December 2018. Benchmark is the buy-and-hold strategy. Panel A reports the annualized excess return (in percent) as well as annualized Sharpe ratio for the benchmark and the market timing strategy. Panel B reports the Carhart (1997) four-factor adjusted alphas of the benchmark and timing strategy where the holding period is one week. Newey-West adjusted t-statistics are given below the portfolio returns in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Summary statistics of the timing strategy									
	Buy-and-hold	1	2	3	4	5	6	7	8
Annualized excess return	-5.68	12.83	11.17	15.09	7.41	10.95	-0.73	-8.94	-16.39
Sharpe ratio	-0.29	0.82	0.42	0.39	0.15	0.18	-0.01	-0.11	-0.18

Panel B. Carhart (1997) four-factor regression					
	Intercept	RMRF	SMB	HML	UMD
Buy-and-hold	0.000	0.960***	0.088***	-0.049***	0.013
t-stat	(0.58)	(94.16)	(4.76)	(-2.56)	(1.09)
Timing strategy	0.002**	0.615***	0.300***	0.073	0.277***
t-stat	(2.32)	(8.49)	(3.40)	(0.95)	(4.15)

Appendix

A.1 Variable Definitions

The variables used for the analysis are described in detail below. They are constructed using data from CSMAR, WIND, Choice, RESSET, HKEX (daily and monthly stock files, quarterly and annual industrial file, northbound capital flows, northbound investors' shareholdings, etc.).

1. Size: Denotes the natural logarithm of the market capitalization at the end of the week for each stock. Size = stock price × the number of shares outstanding, in thousand RMB yuan).
2. BM: Denotes the ratio of book value to market value, where the book value is the common equity plus balance-sheet deferred taxes for the latest fiscal quarter as of the end of the last quarter, and the market value is equity capitalization measured at the end of each week.
3. REVERSAL: Following Da, Liu, and Schaumburg (2014), we define the past short-term reversal as the cumulative return from week $t-4$ to week $t-1$ for each stock-week observation.
4. RUNUP: Following Jegadeesh and Titman (1993), we define the run-up effect as the cumulative return from week $t-52$ to week $t-5$ for each stock-week observation.
5. VOL: Denotes the monthly realized volatility of stock return. We compute this variable as the standard deviation of daily excess market return over the risk-free rate using three-month deposit rate.
6. IVOL: Denotes the idiosyncratic volatility of stock return. Following Ang et al. (2006), we measure this variable as the standard deviation of residuals in the Fama-French three-factor model over the past three months.
7. TURN: Denotes the weekly turnover, which is measured using the ratio of weekly trading volume to shares outstanding in the prior one month.
8. ROA: Denotes the return on assets. This variable is measured as the ratio of net income to average total assets for the prior fiscal quarter ending at least three months ago and no longer than one year.
9. SOE: Denotes a dummy variable identifying state-owned enterprise. SOE equals 1 if the stock is classified as state-owned enterprise in CSMAR and 0, otherwise.
10. MSCI: MSCI is a dummy variable to flag firms listed in the MSCI China index. MSCI (Morgan Stanley Capital International) started to include *some* of large-cap A shares in the MSCI Emerging Markets Index on May 31st, 2018. If one stock is included in the MSCI A-share index, the dummy

variable MSCI equals one after June 2018.

11. InstHold: Denotes the stock share of institutional holding, which is measured as the percentage of stakes in all institutions. The raw measure of institutional holding is disclosed to the public quarterly in China and thus, we use the latest data as of the end of the prior fiscal quarter.
12. AnalyNum: Denotes the number of individual analysts that covering the stock in the year. An analyst is said to be "covering" a stock if he/she has produced a stock recommendation for a given stock in the CSMAR Analyst Prediction database in the past year.

A.2 Robustness checks

We perform a bunch of robustness tests to determine whether the main findings are sensitive to our research design. Some of these tests have been mentioned or footnoted throughout the text, and the rest are discussed here in detail.

First, to address the concern on estimation errors in extreme groups, we repeat univariate portfolio sorts using the back-tested procedure suggested by Mamaysky et al. (2008) in Table I.1 of the Internet Appendix. More specifically, for a stock to be included in a portfolio in week t+2, its return in week t+1 must be below (above) the cross-sectional median if its HPC estimated at the end of month t is below (above) the cross-sectional median. All qualitative inferences from the paper remain unchanged and the cross-sectional predictability of HPC is even more salient in the back-tested sample.

Second, in Table I.2 of the Internet Appendix, we examine daily HPCs. Consistent with main findings, we find that the cross-sectional predictability that we observe is robust to a trading strategy based on the variation of shareholdings among northbound investors at the highest possible frequency. Another concern is that the persistence of return predictability of HPC might be captured by actively seeking out risks characterized by common factors following periods of recent success among northbound investors, we confirm that the benchmark adjusted return spread between top and bottom quintiles sorted by weekly HPC does not reverse in the long run in untabulated results.

Third, as we mentioned in the text, to determine whether northbound flows are purely value investors tracking "good" assets without any motivation driven information advantage, our analysis of portfolio sorts is repeated by using HPC residuals after a bunch of firm-level characteristics, as reported in Table I.3 of the Appendix. We find all results are quantitatively similar. In untabulated results, to determine whether our results are robust to the limited-attention-induced demand pressure explanation for HPC's ability to predict future returns, we repeat stock-level analyses in Table 2 and Table 5 after excluding observations related to daily positions on the daily lists of actively traded stocks. We also use the same proxy, HPC for flow pressure driven by investors' excessive attention instead of *VBHD* in portfolio sorts using the subsample of stocks on lists. We continue to find no return reverse in the long run, suggesting that the cross-sectional predictability of HPC is not just due to domestic demand pressure derived from limited attention and copycat herding.

Table I.1 Back-tested portfolio sorts

To address the concern on estimation errors in extreme groups, we repeat univariate portfolio sorts using the back-tested procedure suggested by Mamaysky et al. (2008). Specifically, for a stock to be included in a portfolio in week t+2, its return in week t+1 must be below (above) the cross-sectional median if its HPC estimated at the end of month t is below (above) the cross-sectional median. This table presents average weekly excess returns (in percent) for value-weighted portfolios constructed using back-tested procedure. Newey and West (1987) three-lag adjusted t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Excess return (%)	t-stat
Low	-0.30	(-0.86)
2	-0.17	(-0.56)
3	-0.46	(-1.51)
4	-0.63*	(-1.83)
5	-0.07	(-0.22)
6	-0.13	(-0.37)
7	0.11	(0.32)
8	0.11	(0.35)
9	0.02	(0.07)
High	0.32	(1.02)
High-Low	0.62***	(2.83)

Table I.2 Cross-section return predictability using residual HPC

This table presents weekly excess returns (in percent) for portfolios constructed by residual HPC over the period March 2017 through December 2018. Residual HPC is the residual of Model (1) in Table 6 i.e., the residual of regressing HPC on Size, BM, ROA, SOE, VOL, IVOL, TURN, REVERSAL, RUNUP, MSCI, InstHold, and AnalyNum. Formation and holding period for portfolio sorting is one week. *t*-statistics are adjusted for heteroscedasticity and autocorrelation using Newey and West (1987) method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Excess return (%)	t-stat
Low	-0.15	(-0.51)
2	-0.16	(-0.58)
3	-0.13	(-0.53)
4	-0.07	(-0.26)
5	-0.12	(-0.53)
6	-0.24	(-0.96)
7	-0.16	(-0.61)
8	-0.17	(-0.69)
9	0.15	(0.61)
High	0.41	(1.57)
High-Low	0.56***	(2.61)

Table I.3 Univariate portfolio sorts (daily rebalanced)

This table presents average daily excess returns (in percent) for value-weighted portfolios calculated over the period March 2017 through December 2018. We repeat the univariate portfolio sorts in Table 2 except that the rebalance frequency is set to be one day. At the beginning of each day, eligible stocks in Shanghai/Shenzhen-Hong Kong stock connect scheme are sorted into decile portfolios on the basis of their previous day's HPCs and held for one day. Newey and West (1987) three-lag adjusted t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Daily excess return (%)	t-stat
Low	-0.08	(-1.24)
2	-0.08	(-1.30)
3	-0.10	(-1.25)
4	-0.10	(-1.24)
5	-0.02	(-0.41)
6	-0.03	(-0.44)
7	-0.14	(-1.52)
8	0.01	(0.23)
9	0.06	(1.12)
High	0.19***	(3.00)
High-Low	0.28***	(7.99)