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Can foreign equity funds outperform their benchmarks? New evidence from fund-holding data for China

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ABSTRACT

We investigate whether foreign institutional investors can outperform domestic benchmarks. Using portfolio holding-based approaches for the Chinese Qualified Foreign Institutional Investors (QFIIs), we identify fund's active manager opinions and information on the future value of stocks. We find stocks actively traded by QFIIs, and stocks with higher deviation from benchmarks (DFB) outperform their benchmarks in the subsequent one to three quarters. Such "hot hand" phenomenon is driven by foreign institutions' investment skill in incorporating stale information rather than fresh information into asset pricing. Our findings shed new light on the roles of foreign equity funds in eliminating mispricing in emerging markets, and provide evidence on rethinking the role of financial intermediation in a capital-controlled economy.

1. Introduction

Fund performance evaluation can be seen as an indirect test of the Efficient Market Hypothesis (EMH), as the EMH implies that even fund managers could not outperform the market in a persistent way (for recent discussions, see, e.g., Cheng and Yan (2017); Cai et al. (2018); Zhang and Yan (2018); Yan and Cheng (2019)). This implication of EMH stands in stark contrast with the rapid growth of active mutual funds over recent decades, which has been documented as a puzzle for mutual funds (French, 2008; Glode, 2011; Pástor and Stambaugh, 2012). Although it seems straightforward, most studies on fund performance evaluation neglect that fact that their results may hinge on the market they choose, as the extent of efficiency may vary from market to market (Dyck et al., 2013; Jacobs, 2016; Yan and Zhang, 2017; Yang et al., 2019). Contrary to most studies focusing on domestic funds[1] from developed markets, we contribute to the debate on fund performance evaluation above using a new data set for the Qualified Foreign Institutional Investors (QFIIs) in China, which is an emerging market and hence presumably of lower market efficiency relative to the developed markets. Since emerging markets in general differ from developed markets,[2] and China's equity market has been ranked as the second largest in the world by capitalization,[3] our results are of particular importance for other emerging markets.

Specifically, we focus on three open question below in this paper. Although foreign funds have often been labeled as momentum investors in the press, there is limited evidence as to the preferences of them in local equity markets (e.g., Froot et al., 2001; Griffin et al., 2004; Richards, 2005). Furthermore, albeit a small but growing strand of literature that

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[1] This strand of literature mostly focuses on the developed markets. For example, Doshi et al. (2015), Crane and Crotty (2018), and Kenchington et al. (2019) focused on domestic funds' performance in the US market. Mateus et al. (2019) focused on domestic funds' performance in the UK market.

[2] See, e.g. Froot et al. (2001); Griffin et al. (2004); Choe et al. (2005); Richards (2005); Fuertes et al. (2016, 2019); Yan et al. (2016); Yan (2018); Yan and Wang (2018).

[3] Among all the emerging markets, China has a relatively long history of foreign investors and a decreasing amount of associated restrictions. Specifically, China has introduced the scheme of Qualified Foreign Institutional Investors (QFIIs) since 2002, and all the restrictions on QFIIs are either removed already or on the schedule to be removed. The quota limitations on QFIIs have been removed since 10th September 2019. The restriction on shareholding percentage for security companies, fund companies and futures companies will be removed on 2020.

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attempts to ascertain whether foreign/domestic funds have an edge,[4] it remains unclear whether funds have 'hot hands' in identifying underpriced stocks,[5] not to mention foreign funds (Eling and Faust, 2010). Finally, there is indeed little consensus on the potential attributions of foreign fund performance. These questions are of particular importance for emerging markets, and the trading of foreign funds is closely monitored in emerging markets (Richards, 2005).

Methodologically, there are two main approaches for fund performance evaluation: either return-based or portfolio holding-based (Ferson, 2010; Wermers, 2011, 2019). Probably due to data availability, most extant performance evaluation studies are return-based, which suffers from theoretical critiques.[6] We take a different tack by using several holding-based approaches[7] for the identification of active manager opinions and diverse pieces of information on the future value of individual stocks. Our portfolio holdings are based on stocks actively traded by QFIIs (Trades) and stocks deviated from the benchmarks (DFB)[8] in China's A-share market[9] over the sample from 1 January 2004 to 31 December 2017. These two active measures can reflect a stronger investment ability than passively following the benchmark index, they also allow us to analyze if active investment by QFIIs can achieve greater return than passive strategies (Chen et al., 2000; Jiang et al., 2014).

We start our empirical analysis by following Falkenstein (1996) as well as Chen et al. (2000) and examining the preferences of QFIIs in China's equity market. Methodologically, we follow the seminal study of Chen et al. (2000) and utilize their three-step approach[10]. By doing so, we do not only find supportive evidence that QFIIs in China are momentum investors (i.e., purchasing past winners and selling past losers), but also find that they prefer small stocks to large stocks, illiquid stocks to liquid stocks, and value stocks to growth stocks. All these characteristics are related to higher average future returns (Fama and French, 1993; Jegadeesh and Titman, 1993; Datar et al., 1998; Lee and Swaminathan, 2000).

We next examine whether foreign funds have 'hot hands' in identifying mispricing in China's equity markets. Following Jiang et al. (2014), we check QFIIs' performance from the stocks deviated from the benchmarks.[11] We consider these stocks held and traded by QFIIs as having superior information about the value of them (Jiang et al., 2014). Active stock trading represents a stronger manager opinion than the passive decision of holding an existing position in a stock (e.g., Chen et al., 2000). Focusing on the performance of their active Deviation From Benchmarks (DFB hereafter)[12] allow us to identify QFIIs' informational advantages (Jiang et al., 2014). We find that the stocks actively purchased (buys) by QFIIs have higher returns than stocks actively sold (sells) by QFIIs, although both Buy and sell positions outperform the benchmarks of Shanghai Composite Index (SHCI) and Shenzhen Component Index (SZCI).

We further check the relationship between stock-level DFB and future returns, and find that stocks with higher DFB have higher risk-adjusted returns relative to their low DFB counterparts. Specifically, the monthly return premium yields a significant difference of 0.7% (equal-weighted) and 0.9% (value-weighted), which remains even after adjusting for various risk factors. For instance, the monthly equal-weighted abnormal returns are 1.89%, 2.26%, 2.24%, 2.44%, 2.11% and 3.22% for the Capital Asset Pricing Model (CAPM), Fama-French three-factor (FF3, Fama and French (1993)), Fama-French-Carhart four-factor model (FFC4, Carhart (1997)), and Fama-French five-factor model (FF5, Fama and French (2015)), Liu-Stambaugh-Yuan three-factor model (LSY3) and four-factor model (LSY4; Liu et al. (2019)), respectively.

Finally, to check whether fresh information or stale information has stronger prediction power, we follow Jiang et al. (2014) to decompose *DFB* into two components: stale information, and fresh information. We identify a cross-sectional relationship between DFB_{t-1} and future abnormal returns in the subsequent one to three quarters within the Fama and MacBeth (1973) cross-sectional regression framework, which suggests that QFIIs behave as informed investors in China's A-share market. It seems that QFIIs rely more on stale information than on fresh information, supporting the argument that foreign investors are skilled in processing stale information (Bailey et al., 2007; Calluzzo et al., 2019; Fjesme, 2019).

Our study extends the literature in several directions. First, in studying the fund preferences for stock characteristics from stock holding data, we add to the studies of, for instance, Falkenstein (1996) and Chen et al. (2000). Unlike their findings that mutual funds prefer larger stocks and growth stocks, we find QFIIs prefer small, value and illiquid stocks in China, all these characteristics are related to higher average returns. Moreover, we provide supportive evidence for the investment skill of foreign equity funds on picking underpriced stocks in China, as stocks actively traded by QFIIs, and stocks have higher deviated from benchmarks (DFB) outperform the market. Our results confirm the value of foreign equity funds in eliminating mispricing in emerging market (Bae et al., 2012; Jacobs, 2016). Whereas the literature focuses on the developed markets,[13] we provide novel insights into fund performance evaluation with data for QFIIs in China. Hence, our study has particular importance for other emerging markets.

In addition, we contribute to the debate on whether active investment

[4] The results are mixed in the extant literature. For instance, Ferreira et al. (2017) use data of 32 countries and find no performance difference between foreign and local investors. Several other studies (e.g., Dvorak (2005) and Agarwal et al. (2009) use Indonesia data, and Hau (2001) use Germany data) find foreign investors underperformed local investors. On the contrary, Froot et al. (2001) and Bailey et al. (2007) find foreigners outperform local investors in emerging markets.

[5] See, e.g., Hendricks et al. (1993); Vidal et al. (2015); Cheng and Yan (2017); Yan and Zhang (2017); Cai et al. (2018); Zhang and Yan (2018); Sha (2019); Sha and Gao (2019); Yan and Cheng (2019).

[6] For instance, i) Roll's criticism. their results can be sensitive to the choice of the benchmark portfolio (Roll, 1978; Chan et al., 2009), ii) alpha-based indicators from return-based approach only provides information about the bargaining position between mutual funds and investors as opposed to the efficiency of financial markets (Berk and Van Binsbergen, 2015) and should be zero in equilibrium (Berk and Green, 2004).

[7] There are too many holding-based studies to be exhausted in this paper (for some interesting cases, see, e.g., Falkenstein, 1996; Wermers, 1999, 2000; Cremers and Petajisto, 2009; Cremers and Pareek, 2016.

[8] The definition of Trades and DFB is provided in Section 3.

[9] There are A-share, B-share and H-share markets in China. The A-share market is the main market in China, and hence we focus on the A-share market in this paper.

[10] First, we calculate both the fraction of a characteristic (e.g., size) for each stock that is held by QFIIs (FracHoldings) and the changes in that fraction during the quarter (Trades), at the end of each calendar quarter for the period from 2004 to 2017. After that, we calculate the equal-weighted average characteristic of a given stock on a given characteristic, and then we sort all stocks by this characteristic at the end of each calendar quarter. We finally assign each stock a rank score on this characteristic, where the rank between zero (low) and one (high).

[11] Our main results are robust to benchmark choices. Regarding the commonly existing benchmark mismatch problem (Sensoy, 2009), we follow Cremers and Petajisto (2009) to select the optimal benchmark which minimizes the average distance between the QFIIs' portfolio weights and the benchmark index weights. We only consider the two most commonly used benchmarks in section 5, but add seven other alternative benchmarks to make sure the robustness of our results in section 6.

[12] The definition of DFB is provided in Section 3.

[13] For instance, to some extent, Vidal-García et al. (2016), Hoberg et al. (2017), Crane and Crotty (2018), and Busse et al. (2019) have demonstrated either short-term or long-term superior performance for mutual funds. However, more studies find that mutual funds tend to underperform their benchmarks (Busse et al., 2010; Barras et al., 2010; Ferreira et al., 2013; Leippold and Rueegg, 2019).

(i.e., derivations from benchmarks and active Trades) by foreign institutional investors can achieve greater return than passive strategies (Huang et al., 2011; Sha, 2019; Yang et al., 2019). Although many studies from the developed markets find that the deviation from benchmarks (i.e., risk-shifting behaviors of the mutual funds) is associated with deteriorated future fund performance (Huang et al., 2011). They implicitly raise the hurdle for the fund managers to improve future performance as developed markets are of high market efficiency (e.g., Yang et al., 2019). In line with this intuition, we find supportive evidence for the alternative conjecture that derivations from benchmarks (i.e., risk-shifting) improve the future performance of foreign funds in China (i.e., QFIIs), which supports the argument that active investment creates values in emerging markets (Dyck et al., 2013; Jacobs, 2016; Yan and Zhang, 2017).

Finally, our paper adds to the literature on the attribution of information to fund performance.[14] Following Jiang et al. (2014) and decomposing our proxy of information (i.e., DFB) into two components, we provide fresh evidence supporting the argument that foreign investors are skilled in processing stale information (Dvorak, 2005; Bailey et al., 2007; Calluzzo et al., 2019; Fjesme, 2019). Our paper adds to the literature on the roles of foreign equity funds on improving the informativeness of stock prices (Bae et al., 2012; Yang et al., 2019).

The remainder of the paper is organized as follows. Section 2 provides a brief background of QFIIs' investment in China. Section 3 describes the data and the measurement variables. Section 4 discusses the empirical results. Section 5 presents robustness analysis. Section 6 concludes. Our main results stay qualitatively the same when we sort stocks into alternative numbers of portfolios, and we selectively delegate some of the results (i.e., results based on quintiles) into the online Appendix for brevity.

2. Background of QFIIs' investment in China's A-share market

The QFII scheme was introduced by the People's Bank of China (PBC), China's Security Regulatory Commission (CSRC), as well as the State Administration of Foreign Exchange (SAFE). Since December 1, 2002, QFIIs can invest directly in China's equity markets on a selective basis. The CSRC issues the QFIIs' license, oversees the transactions, and annually inspects QFIIs and, the SAFE supervises QFIIs' foreign exchange operations (e.g., the issuance of foreign exchange certificates, supervision of account management and foreign exchange settlements).

In the past decades, QFIIs' entry requirements have been gradually relaxed by the CSRC and the SAFE. For example, in addition to China's A-shares, treasury securities, and corporate bonds, since 2011 QFIIs have been permitted to trade stock index futures. The qualification requirements for assets under management by QFIIs have been reduced from USD 10 billion to 5 billion. Restrictions on capital remittance, the investment proportion of stocks of at least 50%, and the requirement of the principal lock period have been eliminated. Since 2018, QFIIs have been permitted to hedge in the foreign exchange market, and since 2019, the quota restrictions on QFIIs have been removed.

The QFII scheme has a history of approximately 17 years, and the number and the aggregate value of QFIIs have expanded steadily. The number of QFIIs increased from 10 in 2003 to 308 in 2018. The aggregate amount of QFIIs' investment in the A-share market increased from USD 20.01 million in 2003 to USD 15,237.75 million in 2018. The number of stocks held by QFIIs increased from 60.36 million in 2013 to 9,254.24 million in 2018, and QFIIs held on average approximately 0.67% of all stocks listed in China's A-share market. At the beginning of 2003, QFIIs held 0.08% of the shares listed in China's A-share market, and QFIIs gradually increased their stockholdings to 1.83% by the end of 2017 (Table 1). In summary, the importance of QFIIs in China's A-share market has increased dramatically over the past 17 years.

3. Data and measurements for active investment

3.1. Data source

According to the trading rules of the CSRC, foreign and domestic institutionally investors release their equity holdings every quarter (Q). Hence, only quarterly stock holdings data of QFIIs from 2004: Q1 to 2017: Q4. QFIIs' investment objective can be bonds, stocks or stock futures are available. We focus on the QFIIs that hold and trade stocks listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). At the end of 2017, there were 308 registered QFIIs and 1201 firms[15] held by QFIIs. We collect the subsequent monthly, quarterly, semiannual and three-quarter returns of stocks held and actively traded by QFIIs. We also collect the related characteristics (e.g., size, BM ratio) of stocks held and traded by QFIIs. All the above data sources are from the WIND financial database (https://www.wind.com.cn) and are free of survivorship bias. All the risk factors excluding LSY3 and LSY4 are from China Stock Market & Accounting Research (CSMAR) database. We obtain the risk factors of LSY3 from Liu et al. (2019), but calculate the sentiment factor in LSY4 by ourselves.

3.2. Measurement of Fracholdings, trades, and DFB

This paper examines the performance of stocks actively traded by QFIIs and the performance of stocks that deviated from benchmarks to evaluate whether QFIIs can outperform the market. We use *FrancHoldings* to check which stocks are most widely held by QFIIs at the end of a given quarter, by following the method of Chen et al. (2000). The *FracHoldings* of stock *i* during quarter *t* is measured as follows:

$$FracHoldings_{i,t} = \frac{Number of SharesHeld_{i,t}}{TotalSharesOutstanding_{i,t}} \tag{1}$$

If QFIIs hold stocks passively rather than trade them actively; thus, the position of this stock held by QFIIs should be invariant. Otherwise, QFIIs managers trade those stocks actively from quarter to quarter. *FrancHoldings* of QFIIs will vary substantially across stocks and quarters. We use *Trades* to measure the quarterly change in the *FrancHoldings* of a stock by QFIIs. Positive (negative) *Trades* of stock *i* refer to net buyers (sellers) of QFIIs in quarter *t*. Specifically, we measure the aggregate value of *Trades* of stock *i* during quarter *t* as follows:

$$Trades_{i,t} = FracHoldings_{i,t} - FracHoldings_{i,t-1} \tag{2}$$

If QFIIs have the same preference as the market portfolio, the percentage level of stocks in QFIIs' portfolio should be the same as in the market portfolio. Otherwise, QFII managers invest in different stocks with different portions (Chen et al., 2000). We assess whether QFIIs deviate from the benchmarks as revealed through their overweighting or underweighting decisions.[16] The DFB of stock *i* during quarterly *t* is measured as follows (Jiang et al., 2014).

[14] For example, some attritions for superior and inferior performance in emerging markets are aggressive trading behavior (Agarwal et al., 2009), informational disadvantage (Dvorak, 2005; Bae et al., 2008) and informational advantage (Froot et al., 2001 Bailey et al., 2007; and Albuquerque et al., 2009). Others based on the developed market find performance persistence attributes to informational advantages (Fjesme, 2019), trading regularity (Busse et al., 2019), managerial skill (Doshi et al., 2015), and stock selection and market timing (Bollen and Busse, 2005; Ferson and Mo, 2016).

[15] Of the 1201 firms, 533 had been held by QFIIs for 3 times or more, and 322 had been held by two or more QFIIs at the same time.

[16] We select nine commonly used benchmark indices: the CSI 300, CSI 500, CSI 800, CSI 1000, the SSE 50, the SSE 180, Shanghai Composite Index (SHCI), Shenzhen Component Index (SZCI) and the SZ 100.

Table 1
Summary Statistics of QFIIs' Investment in China's A-share market.

Year	Fund Count	A-share Market (100 Million)		QFII Holdings of A-share (1 Million)		Proportion of All Stocks Held by QFII %	
	No. of QFIIs	Aggregate Value ($)	No. of stocks	Aggregate Value ($)	No. of stocks	Value	Number
2003	12	5,983.67	1,605.57	20.01	60.36	0.03	0.08
2004	26	5,243.71	1,866.12	119.12	297.00	0.2	0.27
2005	34	4,597.02	2,149.12	543.99	1,520.47	0.94	0.44
2006	52	14,294.15	3,093.77	1,977.09	2,817.94	1.19	0.23
2007	52	55,836.88	4,528.48	1,528.11	1,096.60	0.22	0.38
2008	76	20,592.38	6,491.62	1,020.37	1,921.34	0.28	0.36
2009	93	40,403.28	13,710.26	2,730.64	2,115.31	0.21	0.56
2010	106	42,462.37	18,914.56	3,999.61	4,456.58	0.22	0.51
2011	135	35,003.20	21,875.46	4,088.03	5,126.84	0.25	1.29
2012	207	37,464.03	24,107.54	5,836.76	6,261.16	0.32	0.85
2013	250	38,272.60	29,346.27	8,439.99	8,667.74	0.41	0.70
2014	274	60,000.11	31,785.79	15,972.07	9,967.12	0.45	0.58
2015	289	82,701.62	36,615.56	11,075.14	6,368.08	0.22	0.87
2016	300	78,881.10	40,705.57	14,068.84	7,529.30	0.28	1.05
2017	308	89,597.33	44,649.56	19,614.39	8,584.30	0.32	1.83
2018	308	69,127.11	48,658.07	15,237.75	9,254.24	0.22	0.19

This table reports the summary statistics for the QFIIs' investment in China's A-share market.

$$DFB_{i,t} = \frac{\sum_{j=1}^{N_i} w_{i,t}^j}{N_i} - w_{i,t}^b \tag{3}$$

where N_i is the number of QFIIs whose investment portfolios include stock *i*. Stock *i*'s weight in the QFIIs' portfolio is represented by $w_{i,t}^j$. $w_{i,t}^b$ is stock *i*'s weight in the benchmark index.

We follow Cremers and Petajisto (2009) and select nine common benchmark indices: China Security Index (CSI) 300, CSI 500, CSI 800, CSI 1000, SSE 50, the SSE 180, SHCI, SZCI and the Shenzhen (SZ) 100. According to Table 2, the SHCI and SZCI are the two most common benchmarks, and this is consistent with the anecdote evidence, thus we focus on these two only in Section 4.2 to add robustness. In each quarter, from the nine indexes, we select one index that minimizes the average distance between the QFIIs' portfolio weights and the benchmark index weights.

4. Empirical results

4.1. What kinds of stocks do QFIIs prefer?

QFIIs choose stocks with various criteria. We follow Chen et al. (2000) and examine the preferences of QFIIs in China's equity market. Specifically, we use the following three-step approach and examine size (i.e., market capitalization), book-to-market ratio, momentum, and liquidity (proxied by turnover) of the stocks that QFIIs hold and trade.[17] According to these characteristics, we identify the preferences of QFIIs.

For each quarter from 1 January 2004 to 31 December 2017, we determine the rank score of each of these characteristics for each stock held/traded by QFIIs (*FracHoldings* and *Trades,* respectively). The rank score for a stock is that stock's percentile rank on that characteristic relative to all stocks held or traded by QFIIs. The mean value of all rank scores across all stocks is 0.5 by construction. A turnover rank scores more than 0.5 for a stock means that at least half stocks have a smaller turnover ratio than it.

Table 3 presents the *FracHoldings' deciles* and *Trades'* deciles for each characteristic. We construct the deciles using the following steps. We first rank stocks based on *FracHoldings* and *Trades* separately at the end of each quarter. Next, we assign the least held (or traded) 10% of stocks to decile 10, and the next 10% to decile 9, and so forth. We exclude stocks in which QFIIs have 0 aggregate holdings or make 0 aggregate trades in our sample period. The number of stocks in each of these decile portfolios ranges from 26 at the beginning of 2004 to 1201 at the end of 2017.

On average, QFIIs own 8.93% of stocks in *FracHoldings* decile 1, and they own 0.2% of stocks in Decile 10 (Table 3). The average *Trades* range from 3.74% in the top *Trades* decile to approximately −2.11% in the bottom Decile. The wide dispersion in QFIIs' *Trades* indicates that QFIIs deviate significantly from the market portfolio.

QFIIs prefer stocks with smaller capitalization, as the average size for the bottom (top) decile is 0.66 (0.48). The size rank almost increases monotonically from decile 1 to decile 10. QFIIs also prefer value stocks, as the ratio of book-to-market rank declines from decile 1 to decile 10, although not monotonically. QFIIs prefer past winners. For example, the mean value of the momentum rank of decile 1 stocks is 0.59, and that of decile 10 is 0.50. We also examine the liquidity of stocks held by QFIIs. The turnover score for *FracHoldings* decile 1 is 0.47, compared with a score of 0.60 for decile 9 and 0.54 for decile 10. This finding indicates that QFIIs prefer illiquid stocks on average in China's A-share market, which might because illiquid stocks, on average, earn higher returns than liquid stocks (Datar et al., 1998; Lee and Swaminathan, 2000).

In addition, we analyze the characteristics of *Trades* decile portfolios. The characteristics of the *Trades* decile portfolios are consistent with those of the *FracHoldings* decile portfolios. On average, QFIIs trade small stocks more frequently than large stocks, as indicated by the size ranks across all *Trades* deciles. QFIIs also prefer trading value stocks as shown by the book-to-market ratios, which are 0.61 in decile 1, 0.52 in decile 9, and 0.58 in decile 10. The momentum that ranks across all *Trades* deciles exhibits a distinct U shape, indicating that QFIIs prefer past winners. Finally, the turnover ranks show that QFIIs prefer trading illiquid stocks.

Overall, QFIIs prefer small stocks to large stocks, value stocks to growth stocks, past winners to past losers, and illiquid stocks to liquid stocks. All these characteristics are related to higher average future returns (e.g., Fama and French, 1993; Jegadeesh and Titman, 1993; Datar et al., 1998; Lee and Swaminathan, 2000).

4.2. Do QFIIs have 'hot hands' in identifying underpriced stocks in China?

If QFIIs have stock selection abilities, then stocks widely held, and stocks newly purchased by QFIIs should outperform their benchmarks. Similarly, stocks recently sold should underperform their benchmarks. By contrast, if QFII managers have no stock-picking skills, we should find no relation between stock returns of QFIIs' *FracHoldings* and *Trades* and

[17] Specifically, the book-to-market ratio for each stock during each quarter is the ratio of the book value of equity for that stock at the latest fiscal year end to its market capitalization at the beginning of the quarter. We measure momentum with the compounded return over the six-month period immediately prior to the beginning of the quarter, and turnover is measured as the average daily market trading volume over the previous quarter divided by the number of shares outstanding (Chen et al., 2000).

Table 2
Number (No.) of stocks held by QFIIs for each benchmark.

Year	No. of stocks Held by QFIIs	No. of Stocks in Benchmark of CSI300	No. of Stocks in Benchmark of SSE50	No. of Stocks in Benchmark of SSE180	No. of Stocks in Benchmark of SHCI	No. of Stocks in Benchmark of SZ100	No. of Stocks in Benchmark of SZCI	No of Stocks in Benchmark of CSI500	No of Stocks in Benchmark of CSI800	No of Stocks in Benchmark of CSI1000
2004	48	0	6	12	33	10	8	0	0	0
2005	156	37	21	49	105	22	40	0	0	0
2006	278	120	31	71	182	46	69	0	0	0
2007	343	128	30	83	218	37	56	127	255	0
2008	217	83	10	40	124	24	50	72	155	0
2009	287	76	10	42	153	23	76	103	179	0
2010	391	98	24	56	189	28	130	115	213	0
2011	280	82	15	47	134	22	102	75	157	0
2012	291	81	20	45	131	13	119	70	151	0
2013	439	95	22	51	182	22	202	100	195	0
2014	468	110	27	69	204	31	153	121	231	38
2015	503	107	21	55	202	38	146	108	215	156
2016	534	82	11	38	185	30	238	89	171	173
2017	502	74	5	37	155	26	247	85	159	136

This table reports the number of stocks held by QFIIs for each benchmark: China Security Index (CSI) 300, CSI 500, CSI 800, CSI 1000, Shanghai Security Exchange (SSE) 50, the SSE 180, Shanghai Composite Index (SHCI), Shenzhen Component Index (SZCI) and the Shenzhen (SZ) 100. In each quarter, we follow Cremers and Petajisto (2009) and select one out that minimizes the average distance between the QFIIs' portfolio weights and the benchmark index weights.

Table 3
Characteristics of stocks held and traded by QFIIs.

	FracHoldings or *Trades* (%)	Size	Book-to-Market value	Momentum	Turnover
FracHoldings					
Decile 1 (Top)	8.9341	0.4852	0.6738	0.5879	0.4717
Decile 2	3.6785	0.4664	0.5748	0.5989	0.5018
Decile 3	2.3918	0.5141	0.5213	0.5759	0.5100
Decile 4	1.7915	0.5404	0.5044	0.5705	0.5283
Decile 5	1.3677	0.5557	0.5086	0.5629	0.5561
Decile 6	1.0479	0.5833	0.5072	0.5489	0.5720
Decile 7	0.7871	0.5855	0.5324	0.5394	0.5995
Decile 8	0.5803	0.5448	0.5566	0.5206	0.6127
Decile 9	0.3922	0.5660	0.5460	0.4959	0.6056
Decile 10 (Bottom)	0.2040	0.6579	0.5748	0.4986	0.5423
Trades					
Decile 1 (Top)	3.7406	0.3825	0.6216	0.6041	0.5672
Decile 2	1.3945	0.4741	0.5683	0.5813	0.5771
Decile 3	0.8390	0.5177	0.5591	0.5594	0.6063
Decile 4	0.5288	0.5092	0.5430	0.5506	0.6237
Decile 5	0.2915	0.5705	0.5231	0.5169	0.6008
Decile 6	0.0862	0.7030	0.5332	0.5053	0.4773
Decile 7	0.0053	0.5228	0.5389	0.5025	0.5552
Decile 8	−0.0081	0.6670	0.5195	0.5110	0.4591
Decile 9	−0.2838	0.6493	0.5199	0.5632	0.5142
Decile 10 (Bottom)	−2.1112	0.5320	0.5821	0.6088	0.5169

This table reports the characteristics of stock holdings and trades by QFIIs from 2004 to 2017. We sort all stocks separately by their equally-weighted market capitalization, book-to-market ratio, prior six-month return, and the prior quarter average daily turnover ratio at the end of each calendar quarter.

the returns of benchmarks. However, there are many restrictions on stock short selling for domestic and international investors.[18] Thus, the relationship between returns of stocks sold and returns of benchmarks might not be as expected. We address this issue by comparing the cumulative returns of QFIIs' *Trades* and the cumulative returns of their benchmarks. Stocks actively traded by QFIIs likely represent stronger manager opinions on value than the passive decision of holding existing positions (Chen et al., 2000). We examine the performance of stocks actively traded by QFIIs. In this section, we choose two benchmarks, namely SHCI and SZCI, as these two indices are the most common benchmarks in

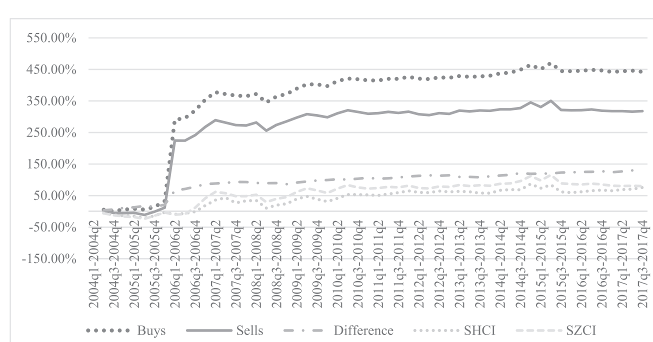

Fig. 1. Monthly Cumulative Return of Stocks Traded by QFIIs. The buys stand for the top quintile portfolio that QFIIs are net buys, whereas sells indicate that QFIIs are net sellers in the bottom quintile. The two benchmark returns are the one-month return of SHCI and SZCI.

[18] There are restrictions on stock short selling in China's A-share market. For instance, borrowing costs are high and the availability of stock to borrow is limited. The only viable way of hedging exposure is through the limited provision of index futures, which is not helpful for individuals trading specific stocks or sectors such as tech and healthcare, which are preferred by QFIIs in China (Zou et al., 2016).

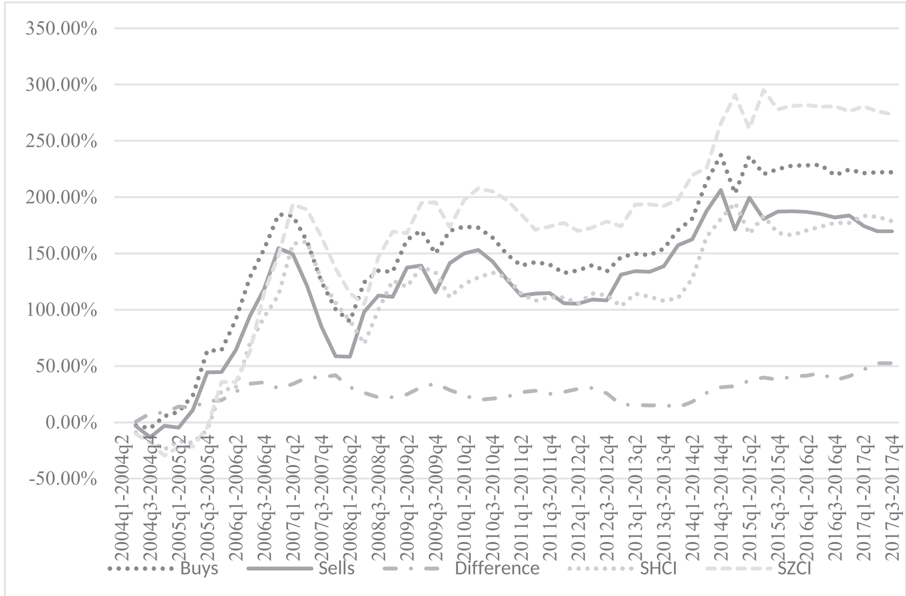

Fig. 2. Quarterly Cumulative Return of stocks Traded by QFIIs. The buys stand for the top quintile portfolio that QFIIs are net buys, whereas sells indicate that QFIIs are net sellers in the bottom quintile. The two benchmark returns are the one-quarter return of the SHCI and SZCI.

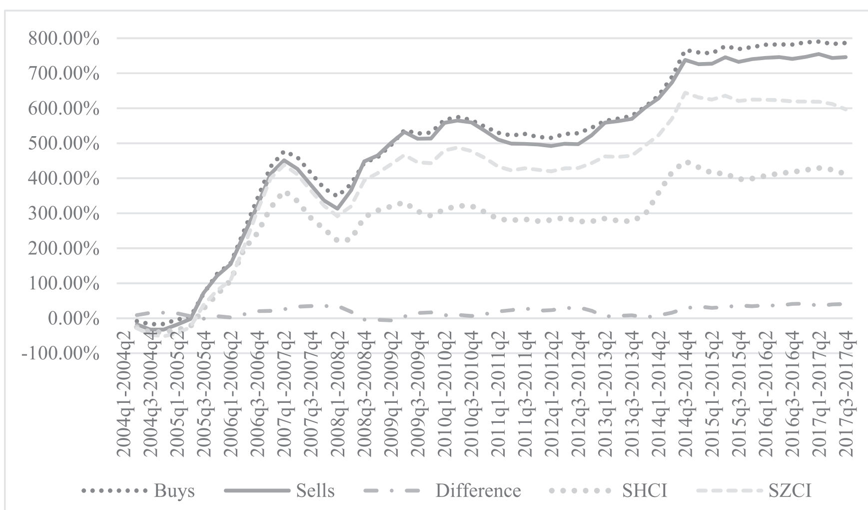

Fig. 3. Semiannually Cumulative Return of stocks Traded by QFIIs. The buys stand for the top quintile portfolio that QFIIs are net buys, whereas sells indicate that QFIIs are net sellers in the bottom quintile. The two benchmark returns are the one-quarter return of the SHCI and SZCI.

practice.[19] We follow Bollen and Busse (2005)'s portfolio ranking approach to calculate the aggregate *Trades* by QFIIs.

We rank stocks based on their quarterly *Trades* by QFIIs. We then compare the cumulative returns of stocks in the top quintile (buys) and cumulative returns of stocks in the bottom quintile (sells) with their benchmarks. We compute the subsequent monthly returns (see also the one-quarter, and two-quarter returns in Figs. 2 and 3) of 'buys' and 'sells' respectively. Specifically, portfolio returns of Buy and sell positions are equally weighted. The differences among Figs. 1–3 refer to the returns of buys minus returns of 'sells'. The subsequent monthly cumulative return difference reaches 125% (Fig. 1). This return difference also exists in the subsequent quarterly and semiannual periods (Figs. 2 and 3), indicating that QFIIs buy past winners and sell past losers. All the returns of 'buys' and 'sells' positions are higher than the benchmark of SHCI throughout the whole period from 2004 to 2017 (Figs. 1–3). There is an exception for the quarterly return of SZCI (Fig. 2). The returns of 'sells' are also higher than their benchmarks, which differs from our hypothesis that newly sold stocks should not outperform their benchmarks. The reason for this finding could be because of the restrictions on the stock short selling system in China, or it might be because *Trades* is insufficiently powerful to identify the outperformance of QFIIs.

4.3. Do deviations from benchmarks forecast QFIIs' future performance?

We further focus on the performance of stocks overweighted or underweighted by QFIIs relative to their benchmarks by following Jiang et al. (2014). On the one hand, the stock-level measure of DFB could

[19] To add robustness to our results, in the next section, we include nine commonly used benchmarks, and we choose one each time that minimizes the average distance between QFIIs' portfolio weights and the benchmark index weights (Cremers and Petajisto, 2009).

Table 4
DFB and Future Stock Returns: quartile Portfolios.

	Panel A: Equal-weighted Post-Ranking Portfolio Return							Panel B: Value-weighted Post-Ranking Portfolio Return						
	Average Return	CAPM Alpha	FF Alpha	FFC4 Alpha	5-Factor Alpha	LSY3 Alpha	LSY4 Alpha	Average Return	CAPM Alpha	FF Alpha	FFC4 Alpha	5-Factor Alpha	LSY3 Alpha	LSY4 Alpha
1	2.298	0.374	−0.380	−0.378	−0.410	−0.502**	−0.423	2.095	0.211	−0.170	−0.189	−0.234	−0.513*	−0.292
	(0.181)	(0.397)	(0.298)	(0.302)	(0.319)	(0.253)	(0.367)	(0.102)	(0.300)	(0.281)	(0.284)	(0.299)	(0.271)	(0.393)
2	2.619	0.987***	0.507*	0.566**	0.464	0.201	0.517	2.427	0.900***	0.605**	0.671***	0.545**	0.206	0.398
	(0.173)	(0.319)	(0.283)	(0.284)	(0.301)	(0.248)	(0.358)	(0.107)	(0.264)	(0.254)	(0.255)	(0.269)	(0.245)	(0.355)
3	2.908	1.806***	1.551***	1.598***	1.444***	1.036***	1.425***	2.536	1.497***	1.035***	1.085***	1.065***	0.745***	1.271***
	(0.177)	(0.262)	(0.259)	(0.261)	(0.272)	(0.261)	(0.376)	(0.110)	(0.301)	(0.271)	(0.273)	(0.288)	(0.234)	(0.334)
4	2.999	2.260***	1.876***	1.866***	2.033***	1.606***	2.796***	2.990	2.293***	1.640***	1.580***	1.843***	1.533***	2.088***
	(0.212)	(0.350)	(0.346)	(0.351)	(0.369)	(0.354)	(0.500)	(0.108)	(0.391)	(0.340)	(0.343)	(0.362)	(0.326)	(0.469)
Q4-Q1	0.701***	1.886***	2.256***	2.244***	2.443***	2.108***	3.219***	0.895**	2.082***	1.810***	1.769***	2.077***	2.046***	2.380***
	(0.022)	(0.041)	(0.035)	(0.036)	(0.038)	(0.034)	(0.048)	(0.012)	(0.038)	(0.034)	(0.034)	(0.036)	(0.033)	(0.048)

This table presents the performance of quartile portfolios formed based on QFIIs' Deviations From Benchmarks (i.e., *DFB*). At the end of each quarter from 2004 to 2017, we sort stocks into quartiles in an ascending order based on *DFB* and compute the average monthly equal-weighted (Panel A) and value-weighted (Panel B) portfolio returns in the following quarter. We also present the risk-adjusted performance (i.e., alpha) of these portfolios, based on the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FFC4), the Fama and French (2015) five-factor model (FF5), and the Liu-Stambaugh-Yuan three-factor, four-factor models (Liu et al. (2019), LSY3, LSY4). We report robust standard errors in parentheses, while ***, **, and * denote statistical significance at 1%, 5% and 10% level, respectively.

reflect QFIIs' investment ability (i.e., if QFIIs aim to outperform a passive benchmark index, they will overweigh stocks they expect to outperform and underweight otherwise, relative to the benchmark); on the other hand, it could aggregate different pieces of information on the future value of individual stocks scattered among QFII managers (Jiang et al., 2014). Our active measure of DFB is designed to capture the informational advantage. If QFIIs managers deviate from their benchmarks for informational reasons, we expect that QFIIs actively manage their investment portfolios by the costly method of acquiring and implementing diverse pieces of information into asset price (Grossman and Stiglitz, 1980; Cremers and Petajisto, 2009; Jiang et al., 2014). Thus, QFIIs with higher *DFB* should receive higher future returns. If QFIIs deviate from their benchmarks and do not have value-related information, the *DFB* should be uncorrelated, or negatively correlated with future stock returns.

We use Bollen and Busse (2005)'s portfolio ranking approach to test the return predictive ability of *DFB*. We rank stocks into quartile based on *DFB* and investigate the succeeding one quarter to three quarters' performances of these quartile portfolios. We rebalance the portfolios based on the updated *DFB* in each quarter. Following Fama and French (2008) and Kothari and Warner (2001), we report both the equal-weighted and value-weighted returns of the quartile portfolios in Table 4[20].

Table 4 suggests that *DFB* strongly forecasts future returns. We present the equal-weighted returns in Panel A and the value-weighted returns in Panel B. We also report the long-short portfolio returns of buying stocks in quartile 4 and selling stocks in quartile 1, which generates statistically significant monthly returns of 0.7% on the equally weighted basis and 0.9% on the value-weighted basis. The t-statistics of these average monthly returns are 31.9 and 74.6, respectively. We further examine whether QFIIs heavily overweight stocks with high returns reveal their willingness to pursue high risks. Because accuracy of risk-adjusted returns depends on choosing good factor models, following Ahmed et al. (2019) and Sha and Gao (2019), we adopt a range of factor models: CAPM, FF3, FFC4, FF5, LSY3, and LSY4, to investigate whether these high returns survive the risk factors.

We present the risk-adjusted returns in columns 2–7 in Panels A and B. The performance of high return stocks over-weighted by QFIIs in line 6, remains large and statistically significant after their loading on various risk factors. The spread returns of long-short portfolios (i.e., longing stocks in quartile 4, and shorting stocks in quartile 1), are both economically and statistically significant after the standard adjustment of the models on the two bases of equal and value weights. For CAPM, FF3, FFC4, FF5, LSY3, and LSY4 models, the long-short return spreads in quartile 4 in excess of quartile 1 deliver the equal-weighted (value-weighted) monthly abnormal returns of 1.89%, 2.26%, 2.24%, 2.44%, 2.11% and 3.22% (2.08%, 1.81%, 1.77%, 2.08%, 2.05%, and 2.38%), respectively. All these risk-adjusted returns are statistically significant, and the t-statistics range from 48 to 65. Our results further indicate that QFIIs are skilled to select stocks with higher future returns. The results are also consistent with other findings that QFIIs possess value-relevant information not fully reflected in stock prices (Bae et al., 2012; Jiang et al., 2014).

4.4. Do QFIIs rely more on stale or fresh information?

To check whether fresh information or stale information has stronger prediction power, we follow Jiang et al. (2014) to decompose *DFB* into two components: the lagged level of *DFB* (DFB_{t-1}), which captures the stale information, and the first difference of *DFB* (ΔDFB_t), which captures fresh information.

$$DFB_t = DFB_{t-1} + \Delta DFB_t \tag{4}$$

[20] For brevity, we only report the monthly returns in Table 4. Readers can send us email for quarterly returns.

Table 5
DFB and future stock returns: Fama and MacBeth (1973) Regressions.

	R_{t+1}						$R_{t\sim t+2}$	$R_{t\sim t+3}$
	1	2	3	4	5	6	7	8
DFB_t	0.312***							
	(6.15)							
DFB_{t-1}		0.287***						
		(3.56)						
ΔDFB_t		0.163						
		(1.25)						
$Q1_t$			– 2.439***	– 1.529**	– 2.191***	– 1.327*	– 4.598***	– 6.185***
			(-4.17)	(-2.19)	(-3.40)	(-1.82)	(3.82)	(-3.45)
$Q4_t$			1.256**	1.177**	1.144***	1.016***	1.340**	2.074*
			(2.39)	(2.60)	(3.96)	(2.87)	(2.47)	(1.68)
$Size_t$				– 0.003		– 0.002	– 0.001	– 0.001
				(-0.52)		(-0.40)	(-0.18)	(-0.08)
BM_t				– 0.415		– 0.538*	– 0.965***	– 0.689
				(-1.32)		(-1.63)	(-2.76)	(-1.27)
$Turnover_t$				– 0.013		0.095	0.251	0.380
				(-0.13)		(0.85)	(1.47)	(1.30)
$Pr1Yr_t$				0.026***		0.023***	0.022*	0.023
				(3.39)		(3.08)	(1.62)	(1.34)
$Pr1M_t$				0.000**		0.000**	0.000	0.000
				(0.032)		(-2.03)	(-0.66)	(-0.89)
MFO					0.175	0.196*	0.277*	0.275
					(1.55)	(1.94)	(1.88)	(1.22)
Intercept	5.757***	5.899***	6.316***	6.812***	6.063***	6.415***	12.731***	20.130***
	(3.88)	(3.99)	(4.29)	(4.33)	(3.93)	(3.97)	(4.93)	(5.41)
Avg Adj – R^2	0.014	0.021	0.020	0.096	0.040	0.112	0.124	0.124

This table presents the Fama and MacBeth (1973) cross-sectional regression results between QFIIs' *DFB* at the end of each quarter and the cumulative risk-adjusted returns over the subsequent three quarters. We follow Jiang et al. (2014) to calculate the control variables: The book-to-market ratio for each stock during each quarter is the ratio of the book value of equity for that stock at the latest fiscal year end to its market capitalization at the beginning of the quarter, while turnover is measured as the average daily market trading volume over the previous quarter divided by the total shares outstanding. Pr1Yr is the past one-year return and Pr1Mt is the past one-month return. MFO is the fraction of shares held by QFIIs. quartile 4 (overweight) and quartile 1 (underweight) are dummy variables, which equals one if the stock is in this quartile with the highest (lowest) DFB and 0 otherwise. The t-statistics in parentheses are computed using the Newey (1) standard errors, while ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

The results in the second column in Table 5 reveal that the coefficient of $DFB_{t\text{-}1}$ is statistically significant (t statistics = 3.56), and that, the coefficient of ΔDFB_t is not (t statistics = 1.25), suggesting that QFIIs rely heavily on stale information rather than fresh information to forecast future returns, which is different from the findings that mutual funds rely on fresh information forecasting future returns in US market (Jiang et al., 2014). The result is consistent with the findings in the literature. For instance, there is evidence that foreign investors have a strategic information advantage and are skilled at processing stale information relevant for asset pricing (Dvorak, 2005; Bailey et al., 2007; Calluzzo et al., 2019; Fjesme, 2019).

5. Robustness check

5.1. Additional test with cross-sectional regression framework

We also investigate the return forecasting power of *DFB* with the Fama and MacBeth (1973) cross-sectional regression framework. We further follow Jiang et al. (2014) and divide *DFB* into two dummy variables: Q1 represents membership in the quartile with the lowest *DFB*, and Q4 represents membership in the quartile with the highest *DFB*. This division has another advantage in that the coefficients of Q1 and Q4 in the Fama and MacBeth cross-sectional regression represent the return differences between stocks in their respective quartile and all stocks in other quartiles (Jiang et al., 2014). The results in columns 3 and 4 (in Table 5) indicate that stocks in quartile 1 obtain significantly negative returns (−2.439 and −1.529, respectively), while stocks in quartile 4 obtain significantly positive returns (1.256 and 1.177, respectively), even after controlling for the effect of firm characteristics such as size, BM ratio, momentum of past one-year return and past one-month return.

We control for other variables that might also affect the future returns of stocks held by QFIIs. Table 5 presents evidence that *DFB* correlates with excess returns in the subsequent quarter. To control for the effect of mutual fund ownership (MFO) on the performance of *DFB* stocks, we also include the proportion of shares owned by QFIIs, denoted by MFO as a control variable in our regressions. Because a high *DFB* reflects a high QFII ownership, the future returns of stocks by QFIIs might also be caused by MFO (Jiang et al., 2014). The results in columns 5 and 6 indicate that MFO in our sample has some impact on future returns (with a t statistic = 1.55 and 1.94), and *DFB* still possesses forecasting power in the subsequent quarter after we further control for MFO and other variables (such as momentum factors as indicated by Pr1Yr and Pr1Mt, liquidity factors as indicated by turnover, BM and size factors). Based on these results, we conclude that *DFB* can strongly and positively predict future stock returns even after controlling for other stock characteristics. The performance of stocks in different *DFB* quartiles indicates that QFIIs behave as informed investors in China's A-share market.

5.2. Performance persistence or price pressure?

There is an alternative interpretation that the higher returns on the stocks with higher DFB could reflect the effect of demand pressure on prices (Jiang et al., 2014). Specifically, if QFIIs exhibit herding behavior and continue to buy stocks that they overweight (Wermers, 1999), the continuous demand from QFIIs could cause stock prices above equilibrium levels and lead to higher in-sample returns. If high returns of stocks with high DFB mainly attribute to value relevant information, there should be no subsequent return reversal. Otherwise, we expect to observe subsequent return reversal (Jiang et al., 2014).

We further check the relationship between the abnormal returns of the subsequent two to three quarters and DFB. The results in columns 7 and 8 indicate that the positive correlation between *DFB* and future abnormal returns persists in the subsequent two to three quarters, with no sign of return reversal. Thus, *DFB* seems to predict the returns based on the value-relevant information collected from diverse mutual fund managers, as revealed through their overweighting or underweighting of investment decisions. Our results confirm that QFIIs predict future stock returns based on value relevant information.

6. Conclusion

Contrary to most studies focusing on domestic funds from developed markets, we examine the preference and performance of the foreign equity funds in emerging market with a panel data set of 308 QFIIs in China's A-share market over the time period 2004–2017. We focus on stocks actively traded by QFIIs, and stocks deviated from the benchmarks (*DFB*), as they can reflect a stronger investment ability and diverse pieces of information on the future value of individual stocks.

Our analysis on the performance of stocks Trades and stocks DFB uncovers a dramatic investment skill of QFIIs. First, QFIIs prefer small stocks to large stocks, lower liquidity stocks to higher liquidity stocks, and value stocks to growth stocks. All these characteristics are related to higher average future returns. Secondly, we find that the stocks actively purchased (buys) by QFIIs have higher returns than stocks actively sold (sells) by QFIIs, both buy and sell positions outperform the benchmarks of Shanghai Composite Index (SHCI) and Shenzhen Component Index (SZCI). This return difference also exists in the subsequent quarterly and semiannual periods, indicating that QFIIs buy winners and sell losers. We further find that stocks with higher DFB have higher risk-adjusted returns relative to their low DFB counterparts, performance persistence in the subsequent one to three quarters, and QFIIs rely on stale information rather than fresh information. These results are consistent across our main analyses and a battery of robustness checks including five main-stream factor models (the LSY3, LSY4, FF3, FFC4 and FF5 model), two weighting schemes (equal-weighted and value-weighted), two benchmarks versus nine benchmarks, deciles versus quartiles versus quintiles, a portfolio-sorting approach versus the Fama and MacBeth (1973) cross-sectional regression framework, and many control variables.

Due to data limitations, one topic of great interest that we have not addressed is whether QFIIs can still add value, if transaction costs, expenses, taxes, and so forth are considered. We firmly believe this fruitful further research direction would advance the literature.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2020.04.025.

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