Quantitative Finance and Economics

QFE, 7(4): 595–621.
DOI: 10.3934/QFE.2023029
Received: 16 June 2023
Revised: 30 October 2023
Accepted: 02 November 2023
Published: 14 November 2023

http://www.aimspress.com/journal/QFE

Research article

Do fund managers in the Chinese mutual fund market deliver positive risk-adjusted returns? Yes, but it is mainly observed for local fund managers

Julius Nickelsen and Olaf Stotz*

Frankfurt School of Finance and Management, Adickesallee 32–34, D-60322 Frankfurt am Main, Germany

*** Correspondence:** Email: olaf.stotz@gmx.de.

Abstract: A bootstrap and a subsequent injected alpha analysis were conducted on 1,221 Chinese mutual funds that were active at some point between July 2001 and July 2021. The results show that most active managers achieve a positive risk-adjusted return. Additionally, we find that this phenomenon is primarily attributable to local (i.e., Chinese) fund managers. We argue that one explanation for the different levels of risk-adjusted returns observed is the information asymmetry between foreign and local fund managers. Additional results support this view, as fund managers primarily investing in small- to mid-cap and value stocks provide a superior performance, which inherently exhibit greater information asymmetry. The findings are contrary to those from similar studies in developed markets, where only a few active managers demonstrate actual skill in their performance.

Keywords: Skill versus Luck; active management; bootstrap methodology; injected alpha; Chinese mutual fund market; investment styles; information asymmetries

JEL Codes: G11, G23

1. Introduction

In the long tradition of analyzing the performance of asset managers, a central focus has been determining whether asset managers have sufficient skill to deliver reliably positive risk-adjusted returns or if the positive alphas observed result from luck alone. Empirical evidence from developed fund markets, like the US, mainly supports the latter argument (e.g., Fama and French, 2010). In this paper, we analyze whether less developed markets display similar characteristics in their alpha distribution.

We investigate this issue in the Chinese fund market and expect to find a different distribution of alphas than that observed in developed markets. The institutional setting in the Chinese market is different from developed markets because institutional investors, on aggregate, hold a lower share of Chinese stocks than retail investors (see, for example, Kutan et al., 2018). In addition, Titman et al. (2021) report that almost 90% of the daily trading volume of China's stock market comes from retail investors. This makes the Chinese stock market less efficient and provides stock selection opportunities for investors with better investment skills (see Deng and Xu, 2014).

We argue that local fund managers in China should generate a higher alpha than their foreign competitors when investing in Chinese equities. Underlying this argument is the notion that Chinese asset managers have better access to information than foreign investors, given that there are more formal and informal barriers to information in the Chinese stock market compared to the US (see, e.g., Seddighi and Nian, 2004, Fifield and Jetty, 2008). A simple example of this is evident in the recent study by Corbet et al. (2020). The authors posit that domestic investors in China recognized the severity of the Covid-19 pandemic at a much earlier stage due to their local proximity to the initial outbreak. This timely realization on the part of local participants allowed them to react to the inevitable market correction well ahead of foreign investors, ultimately leading to better overall performance.

There are additional reasons why geographic proximity to an investee company may be beneficial. In general, local investors and analysts should have a local information advantage (Malloy, 2005). Foreign managers are disadvantaged since they are less familiar with laws, regulations and cultural issues than locals (e.g., Chan et al., 2005). Geographical distance can act as a barrier to cultural exchange (e.g., Portes and Rey, 2005). Ownership at a distance also leads to higher costs for analyzing and monitoring an investee company (e.g., Ayers et al., 2011). Local investors' closer geographic proximity should, therefore, enable them to perform better. Chung et al. (2021) provides empirical support for this hypothesis. They demonstrate that ownership by Chinese institutional investors predicts a higher stock return than US ownership. Also, some Chinese companies have issued different classes of shares (i.e., A-shares and H-shares) and there have been regulatory restrictions for foreigner to invest in A-shares. Although some of these restrictions have been removed in the past (e.g., Li et al., 2015) Chinese and foreign managers might still have a different universe of investable securities. The correlation between geographical proximity and performance related to institutional ownership is a widespread phenomenon. Ferreira et al. (2017) find similar results for a sample of 32 countries, and Wagner and Margaritis (2017) provide evidence for emerging market fund managers.

While these impacts of geographical proximity, information asymmetries, familiarity with laws and regulations and lower monitoring costs should apply to the entire mutual fund market, we suspect that they may be more pronounced in specific market segments, such as those with particular size- or value-based investment styles. The rationale here is that obtaining valuable information on small- or mid-cap Chinese stocks could be more challenging than for large-cap companies. Additionally, foreign investors might have concerns about investor protection issues and governance problems in Chinese small- or mid-cap companies. Leuz et al. (2008) document that governance issues are one reason why non-domestic investors invest less effectively abroad than in their home markets. Furthermore, the identification of value stocks requires in-depth knowledge of the Chinese accounting system because valuation ratios are often derived by relating the market price to accounting data, such as the book value of equity (Fama and French, 1993).

In contrast, picking winners in the large-cap and growth domains is more difficult because there is more information competition for large-cap stocks (i.e., greater analyst coverage), and identifying winners across growth stocks is challenging since empirical research shows that growth is difficult to forecast in general (e.g., Cochrane, 2011). The distribution of risk-adjusted alphas in different investment styles has yet to be thoroughly investigated. Agyei-Ampomah et al. (2015) make one of the few contributions to this research area, providing support for paying particular attention to stock size and value. Their results indicate that between 1990 and 2011, there was more skill exhibited by US funds focused on small and mid-cap companies than among funds focused on large caps and more skill in value-oriented than growth funds. For emerging markets, Wagner and Magaritis (2017) document that managers of growth funds seem to add value.

The main contribution of this paper is our analysis of the distribution of risk-adjusted alphas in the Chinese market, with particular attention to domestic or local fund managers in two market segments: small- and mid-cap versus large-cap and value versus growth stocks. We analyze these questions using the bootstrap methodology introduced by Kosowski et al. (2006) and further developed by Fama and French (2010) and others. Our main result supports the hypothesis that, in China, the group comprising local fund managers contains a larger proportion of fund managers providing risk-adjusted returns than the group comprising foreign managers. The distribution of alphas (net of fees) for foreign fund managers, however, seems not dissimilar from the luck distribution. With respect to fund managers in the small- and mid-cap and value domains, we find that the difference in alphas between local and foreign managers is substantial.

Our findings thus contribute to the literature in three main ways. First, our results suggest that the distribution of alphas among fund managers in developing mutual fund markets with potential information asymmetries appears to differ from that of developed markets like the US. Studies on the US mutual fund market mainly indicate that alphas are distributed with a mean of zero (below zero) before (after) costs and the distribution is indistinguishable from one generated by luck alone. Consequently, the presence of skill in a developed mutual fund market lacks robust data support. However, the results for the Chinese mutual fund market imply that fund managers can achieve a positive alpha after costs. Second, the domicile of the manager’s company is simply a priori information that helps differentiate managers with higher alphas from those with lower alphas. We find that local fund managers achieve a substantially higher alpha than foreign ones. A retail investor seeking to buy a mutual fund in the Chinese market can benefit from this information. Third, our results suggest that managers of small and mid-cap, as well as value funds, particularly those who are local, constitute a larger proportion of positive alphas than managers of other funds.

The remainder of this paper is organized as follows. In Section 2, we review the literature. In Section 3, we briefly introduce the methodology. In Section 4, we describe the dataset and present our main results. Section 5 contains a discussion of our findings. In Section 6, we conclude.

2. Literature review and hypothesis development

The analysis of whether asset managers possess stock selection skills can be traced back to Jensen (1968), who proposed a regression approach relating a fund's excess returns to those of the market. Additional factors were subsequently included in the regression, such as size, value and momentum, as in Carhart (1997). However, observing significant alphas in these regressions does not prove the existence of stock selection skills. The significant alphas of some fund managers could be purely due to luck. Therefore, to draw (statistical) inferences about whether the proportion of significant alphas within a group of fund managers is greater than what would be expected by pure luck, the distribution of alphas and their corresponding t-statistics must be analyzed.[1]

This idea is formalized by Kosowski et al. (2006), who compare two distributions of the funds' alpha t-statistics. The actual distribution of these t-statistics in the US mutual fund market is compared with the "luck" distribution obtained by a bootstrap methodology. Two major improvements of the bootstrap approach are introduced by Fama and French (2010). The authors enhance the bootstrap methodology by randomly sampling the entire cross-section, allowing them to consider the cross-correlation of fund returns, while Kosowski et al. (2006) bootstrapped the data fund by fund.[2] Fama and French (2010) expand the luck versus skill[3] analysis with their injected alpha method, described in greater detail below. Their main conclusion is that, in the US equity fund market, the actual distribution of alphas is not significantly different from one based on luck. Other developed markets like Germany (e.g., Cuthbertson and Nitzsche, 2013), Japan (e.g., Pilbeam and Preston, 2019) or the UK (e.g., Blake et al., 2017) provide further support for this conclusion.

However, the evidence from emerging markets is mixed. Suh and Hong (2011) analyze the Korean mutual fund market and find that about 60% of all active managers demonstrated actual skill. Parshakov (2014) applies a bootstrap methodology to the Russian mutual fund market, finding little evidence of skill. In the Chinese market, which is the focus here, the evidence is also mixed. While the newly developed methodology of Cornell et al. (2020) suggests that Chinese fund managers have

[1] It's important to note that Berk and van Binsbergen (2015) argue that alpha, as a measure of skill, might not be suitable. Instead, they suggest using alpha multiplied by the assets managed by fund managers.

[2] Recently, Harvey and Liu (2020) proposed a double-bootstrap method that allows us to address the trade-off between Type I and Type II statistical errors of the alpha estimate simultaneously, whereas the method of Fama and French (2010) primarily controls Type I error. In other words, Harvey and Liu's method enables the reduction of one error type while increasing the alternative error type. We follow Fama and French since their approach should result in fewer Type I errors.

[3] Fama and French (2010) classify a distribution of risk-adjusted alphas with a positive mean as indicative of skill. In the introduction, we argued that positive alphas can arise from asymmetric information or differing access to securities between Chinese and foreign managers. In such scenarios, a positive alpha doesn't necessarily reflect skill. Consistent with Fama and French (2010), we also employ the term "skill" when a distribution of alphas exhibits a positive mean. We thank an anonymous referee for clarifying this point.

investment skills, standard regression approaches Carhart (1997) provide mixed evidence for the skill hypothesis. For example, the results of Kiymaz (2015) and Rao et al. (2018) support the notion that Chinese fund managers are skillful, while the analysis of Gao et al. (2020) finds no evidence of investment skills.

The evidence from the bootstrap methodology is also mixed. Yang and Lui (2017) use Fama and French's (2010) bootstrap methodology to analyze 773 Chinese mutual funds for the period 2002 to 2013. They find that only a few funds can outperform their value-weighted market portfolio and subsequently conclude that this number is too small to support the presence of skill. Gao et al. (2021) support this position on skill among investment managers. In contrast, Koutmos et al. (2020) analyze data for the period 2007 to 2015, finding that around 7% of all funds exhibited skill while only 0.2% were unskilled. Given that relatively unskilled retail investors dominate the trading of Chinese stocks in the local stock market (see Titman et al., 2021), this provides opportunities for investors with better investment skills (see Deng and Xu, 2014). Therefore, we re-examine the positive alpha hypothesis as hypothesis 1: Fund managers in the Chinese mutual fund market display a significant level of positive risk-adjusted alphas.

Most of the fund-return studies analyze investment skills in the total cross-section of all fund managers. However, they usually do not ask whether different groups of fund managers exhibit different levels of alphas, which may explain the mixed evidence on risk-adjusted performance measures discussed above. We have argued in the introduction that several factors potentially favor local over foreign managers (e.g., information advantages, familiarity with law and regulation, geographical proximity to investee firms, different access to stocks and effective monitoring of local companies). However, there are also potential arguments why foreign fund managers may have superior investment skills. If a foreign institution has, for example, better information processing abilities due to better general investment experience or better-educated employees (Grinblatt and Keloharju, 2000), it might be expected to outperform domestic investors. However, we suspect that these factors are of minor relevance and not easily applicable in the Chinese market, given the importance of political influence with the government and social networks within the country (e.g., Liang et al., 2021). This leads to hypothesis 2: Local fund managers exhibit a higher level of alpha than foreign managers.

Information asymmetry makes it challenging for foreign fund managers to validate the limited available data in general, but it is likely that this asymmetry will have a more significant effect in some market segments. For small- and mid-cap stocks, information is harder to obtain than for large-cap companies since competition for information in the large-cap segment is higher (e.g., there is more analyst coverage). Therefore, we conjecture that there is a distinct difference in the distribution of alphas in the small- and mid-cap domain between domestic and foreign asset managers. We analyze the disparities observed in this domain and the large-cap segment by testing hypothesis 3: The proportion of local small and mid-cap fund managers exhibiting a positive alpha is greater than that of foreign managers.

In general, emerging markets are relatively new to foreign investors and harder to access (e.g., Fifield and Jetty, 2008). This is particularly true for the Chinese market since foreign investors are less familiar with laws and regulations, such as those pertaining to the accounting system (e.g., Chan et al., 2005). Investment strategies that require such specific knowledge might be differently affected by a fund manager's potential skill. We suspect that value strategies are particularly impacted by these potential skills since valuation ratios usually relate the market value of a company to a fundamental value derived from accounting variables. We assess the value versus growth investment style by testing hypothesis 4: Local value managers exhibit a larger share of positive alphas than foreign managers.

3. Materials and methods

3.1. Bootstrap methodology

To distinguish luck from skill in the cross-section of fund managers, we use the bootstrap methodology introduced by Fama and French (2010). This approach compares the actual distribution of skill (measured by alpha) with a corresponding luck distribution. We estimate a fund's alpha and its associated t-value using the five-factor model in Fama and French (2015):

$$R_i - R_f = \alpha_i + \beta_1(R_{mkt} - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i \quad (1)$$

where,[4] R_i is the monthly return of fund i; R_f is the risk-free rate; α_i is the alpha of fund i; R_{mkt} is the monthly return of the market portfolio; SMB is the monthly return of the size-factor portfolio; HML is the monthly return of the value-factor portfolio; RMW is the monthly return of the quality factor portfolio; CMA is the monthly return of the investment factor portfolio; and ε_i is the residual term.

The luck distribution is generated by assuming that each mutual fund's performance can be attributed to luck alone. That is, the true alpha is set at zero by subtracting the funds' individual alphas from their respective monthly returns. The luck distribution can then be calculated in terms of net and gross returns. Setting the true alpha at zero for net returns implies that, on average, all managers are capable of covering their entire costs (i.e., management fees). For gross returns, setting the true alpha at zero indicates that managers, on average, only possess enough skill to cover costs not included in the management fees (Fama and French, 2010). In our empirical analysis, we focus on net returns.

After subtracting the alpha from the respective monthly fund returns, the final part of the bootstrap approach comprises four steps:

1. A new return series is constructed by randomly drawing a month from the total sample of 241 months (between July 2001 and July 2021). In line with Fama and French (2010), the returns of all funds (and factor portfolios) in the randomly drawn month are selected as the first returns of the respective simulated return series, allowing consideration of the cross-correlation structure of funds.
2. The process of selecting a random month is repeated 241 times until, for each fund and factor portfolio, a new return series is constructed over the same time horizon as the actual return series.
3. All new fund series are regressed against the factor portfolio returns to obtain the first simulated alpha and t(α) distribution.
4. Steps 1–3 are repeated 10,000 times.

All simulated distributions are finally combined into the simulated luck distribution. The main advantage of the bootstrap method lies in the properties of the resulting distribution. Given that the

[4] For readability, we omit time index *t*.

actual fund returns are the basis for every simulation run, the outcome of the bootstrap method has the same properties as the actual distribution. Therefore, it is a better approximation of the distribution of t(α) in a world of pure luck than a normal distribution. However, the methodology does come with its disadvantages, as there is a lower bound on the number of observations a fund can have to be included in the cross-section and determining skill from luck is more qualitative than quantitative.

Finally, we compare the actual and the average simulated luck distribution. The procedure described in this paragraph is applied to the entire cross-section and to the different sub-cross-sections (local vs. foreign, small- and mid-cap vs. large-cap, value vs. growth) to analyze hypotheses 1 to 4.

3.2. Injected alpha methodology

If there are no or just minor differences between the actual distribution and the simulated one, the true alpha in the fund market is likely zero, meaning that performance is dictated by luck. If, however, there are observable differences between the two distributions, the actual distribution of true alpha in the market must be determined. The injected alpha methodology, introduced by Fama and French, aims to find the mean zero normal distribution that captures the extreme ends of the actual distribution. The methodology follows the same steps as the bootstrap method described earlier, with one additional step. A normally distributed alpha with a zero mean and a set standard deviation is randomly drawn and "injected" back into the fund returns. The standard deviation of this alpha then changes in 0.25% increments, starting from 0.25%, to find the sigma value that captures the ends of the tails of the actual distribution. Thus, note that despite the ambiguous name of the methodology, the generated luck distribution still retains the property of an alpha of zero. The result of the methodology is the values of the standard deviation that would explain the observed fund alphas.

In addition to the normally distributed injected alpha, a scalar is added to the equation to account for the different levels of diversification among funds following the practice first introduced by Fama and French (2010). The rationale for adding the scalar is that more diversified funds usually find it harder to outperform the market than less diversified ones. Note that this procedure comes with its drawbacks, since it imposes the actual alpha distribution to have a mean of zero and to be normally distributed, which is not supported by empirical data.

4. Data and empirical results

4.1. Data

The sample period spans from July 2001 to July 2021 due to data availability for mutual funds. The estimation of parameters in Equation (1) requires data on the stock market index and factor portfolios. The market portfolio consists of two stock indexes. For the period July 2001 to November 2008, the total return of the MSCI China Index is used to depict the Chinese market. For the period after November 2008, the broader MSCI China All Shares Index is used. In contrast to the MSCI China, this incorporates all China-A shares, B-shares, H-shares, Redchips, P-chips and foreign listings (e.g., ADRs) and better represents the entire Chinese market.[5] The MSCI benchmarks were chosen over a value-weighted market portfolio as they are the indices most used in practice and allow for a better comparison with the results of active managers. In line with Yang and Lui (2017), the yield of China's 1-year fixed deposit rate was used as the risk-free rate from July 2002 until the end of the period. The risk-free rate of emerging markets from the Kenneth French Data library was used for the period before that.

Factor portfolios SMB, HML, RMW and CMA are not available for the Chinese stock market on the Kenneth French homepage. Therefore, we construct those factors following the (2x3) method in Fama and French (2015) using Bloomberg's database for return construction. The factor portfolios SMB, HML, RMW and CMA are calculated based on Bloomberg financial data for all companies listed in Shanghai, Shenzhen and Hong Kong during the given period. Table 1 presents the monthly average, standard deviation and associated t-values for the sample.

Table 1. Descriptive statistics of factor portfolios and averages of all equity funds in the Chinese stock market.

	Factor returns						Average of all funds	
	R_{mkt}	R_f	SMB	HML	RMW	CMA	Net	Gross
Average return	0.78	0.21	0.50	0.15	−0.01	−0.10	0.86	0.96
Standard deviation	7.30	0.06	4.22	4.93	2.85	2.12	6.27	6.26
t-statistic	1.65	57.69	1.84	0.47	−0.05	−0.75	2.13	2.38

Note(s): Monthly average of the market portfolio R_{mkt}, the risk-free rate R_f and the factor portfolios SMB, HML, RMW and CMA and average monthly (net and gross) return of all mutual funds (N=1,221).

The sample of equity funds includes all Chinese mutual funds which are classified by Bloomberg as actively managed. The sample includes both existing and closed funds; survivorship bias should thus be mitigated. We require funds to have at least 36 months of performance history to obtain a meaningful alpha from the time-series regression in Equation (1) of Fama and French's (2015) five-factor model. This requirement may introduce some survivorship bias in the data set. This bias is difficult to eliminate as reducing the number of months of history required leads to alpha estimates with lower precision and, accordingly, a low t(α) and knock-on effects on the bootstrap methodology. Average monthly returns (gross and net, in US-$), standard deviations and t-statistics are displayed in the second-to-last column in Table 1.

In sum, the sample of Chinese mutual funds comprises 1,221 equity funds. Our sample includes only equity mutual funds with a geographical focus on China (as specified by Bloomberg). Out of the 1,221 funds in the entire cross-section, 528 are managed by Chinese managers, 693 by managers from the rest of the world, 365 by managers focusing on small and mid-cap companies and 551 with managers focusing on large-cap companies (see Table 2. The distinction between Chinese and foreign

[5] It should be noted that access of domestic and foreign investors to Chinese A-shares and H-shares was restricted before 2007 (see, for example, Li *et al*., 2015). This regulatory restriction led to price differentials between A-shares and H-shares (e.g., Li et al., 2006). Since we have no access to the holdings of mutual funds, we cannot address this issue in our analysis. Therefore, no analysis was carried out on the individual holding level.

managers is made based on Bloomberg's criterion "manager domicile". The Chinese group includes both Chinese and Hong Kong managers. We note that on average, there is no material difference in the management fees between Chinese and foreign managers, which is consistent with previous research (see, for example, Wagner and Margaritis, 2017). The average management fee of a Chinese fund is 1.186% p.a., while the average fee charged by foreign managers is 1.172%. Therefore, differences in net alpha between the two groups will translate to the gross alpha level.

Table 2. Number of equity funds in total sample and sub-samples.

	All	Growth	Value	Large Cap	Small/Mid Cap
Chinese	528	67	34	177	226
Foreign	693	351	25	374	137
All	1,221	418	59	551	363

4.2. Descriptive statistics

We start our empirical analyses by looking at the aggregate mutual fund market. Therefore, we form an equally weighted mutual fund portfolio of all 1,221 funds in our sample and present in Table 3 regression results of Fama and French factor portfolios using all months in the sample period.

Table 3. Regression outcomes for an equal-weight portfolio of Chinese equity funds.

	12α		$R_{mkt} - R_f$	SMB	HML	RMW	CMA	R^2
	Gross	Net						
Coef	5.74	2.05	0.81					0.89
t(Coef)	3.21	1.29	44.40					
Coef	4.23	0.72	0.83	0.17	−0.01			0.91
t(Coef)	2.51	0.48	47.73	5.51	−0.48			
Coef	5.39	1.13	0.80	0.12	0.00	−0.09	−0.19	0.91
t(Coef)	3.30	0.75	42.21	2.82	0.01	−1.29	−2.99	

Note(s): Annualized α of the equal-weight portfolios for gross and net returns showing the regression coefficients for the different factors $R_{mkt} - R_f$, SMB, HML, RMW and CMA. The last column contains the adjusted R^2.

In all regressions, the annualized gross alpha of the portfolio is above 4% and statistically significant with a t-value above 2. This suggests that, before management fees, Chinese equity funds seem to deliver a positive risk-adjusted return. However, the annualized alpha of the net return paints a different picture. Although the portfolio does outperform the market portfolio by quite a margin, none of the net alphas are statistically significant. Overall, the analysis of the average mutual fund portfolio suggests that the performance delivered by mutual fund managers in the Chinese market is not as bad as in countries like the US, for which most studies point to negative alphas (e.g., Carhart, 1997) and is consistent with recent research such as Wagner and Margaritis (2017).

4.3. Hypotheses testing

We discuss hypothesis 1 (fund managers in the Chinese mutual fund market display a significant level of positive risk-adjusted alphas) in detail with additional sensitivity analysis. We provide a graphical analysis comparing the actual alpha distribution with the corresponding simulated (luck) distribution. We then present a more formal analysis through test statistics, following the methodology of Fama and French (2010). We implement the corresponding injected alpha method to estimate the quantitative skill level. The remaining hypotheses are then considered in a more concise form by comparing the actual skill and simulated luck distribution, focusing on graphical analysis and main test statistics. Details on the test statistics are summarized in an Internet Appendix.

4.3.1. Skill versus luck in the cross-section of all Chinese mutual funds (hypothesis 1)

We first analyze hypothesis 1 that fund managers in the Chinese mutual fund market display a significant level of positive alphas. Figure 1 below graphically depicts the results of the bootstrap simulation using a kernel density function. The solid black line represents the simulated luck distribution, and the dashed line shows the actual distribution of the t-value of alpha (t(α)), the intercept estimate of Equation (1). A large proportion of fund managers exhibit uniform outperformance, with a majority of the t(α) values being greater than zero. Compared with the luck simulation, some fund managers indeed perform substantially better than luck would suggest.

Kernel density function of simulated and actual $t(\alpha)$

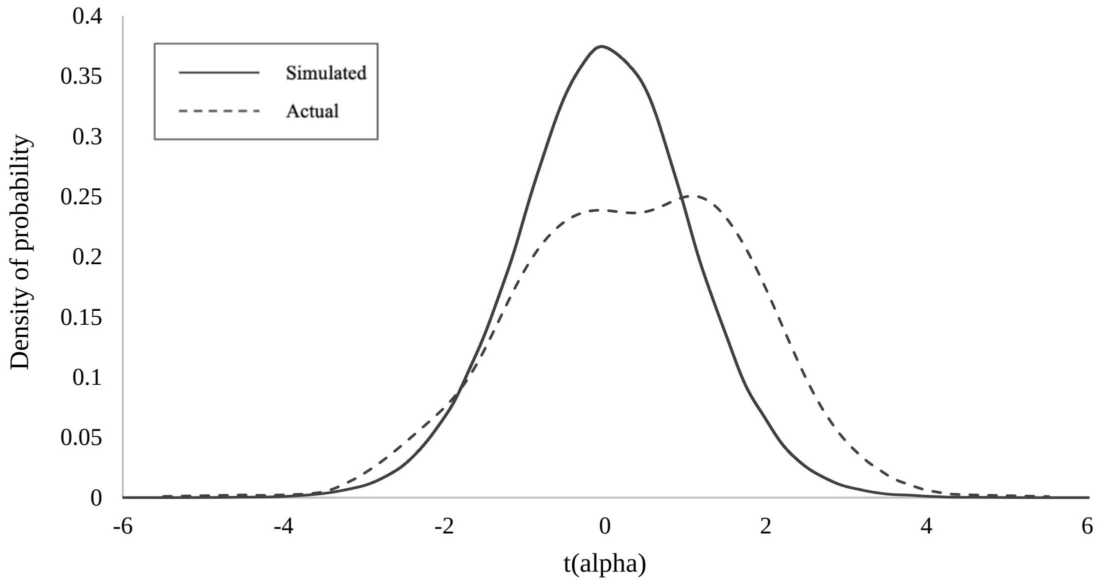


Figure 1. Kernel density function of simulated and actual t(α) for the entire sample cross-section of mutual funds (net returns).

On the left side of the distribution, however, the dashed line is marginally to the left of the solid line, implying that a minority of managers perform worse than luck would suggest. The figure also exhibits two humps, one slightly below 0% and the other at about 2%, indicating that skill is not normally distributed. These results are consistent with the regression results for an equally weighted portfolio of all Chinese stock funds, set out in Table 3. In the next section, we show that separating the sample into local and foreign fund managers helps explain this pattern.

Figure 2 shows the cumulative distribution function of the simulated and actual t(α) values. Similar to Figure 1, the simulated values are represented by a solid line, and the dashed line represents the actual values in the sample. The more to the right the dashed line, the clearer the evidence that outperformance may be attributed to skill rather than luck. Figure 2 shows that from the 20th percentile onward, fund managers perform slightly better than luck would suggest.

At the median, where the simulated distribution crosses the vertical axis by design, the actual distribution is already at a t(α) value of 0.40 (while the luck distribution has a value of zero). The dashed line crossing the vertical axis at the 40th percentile also indicates that there are more fund managers outperforming than underperforming the benchmark. The gap between results based on luck and those of actual managers continues to widen until the 70th percentile, remaining sizeable thereafter.

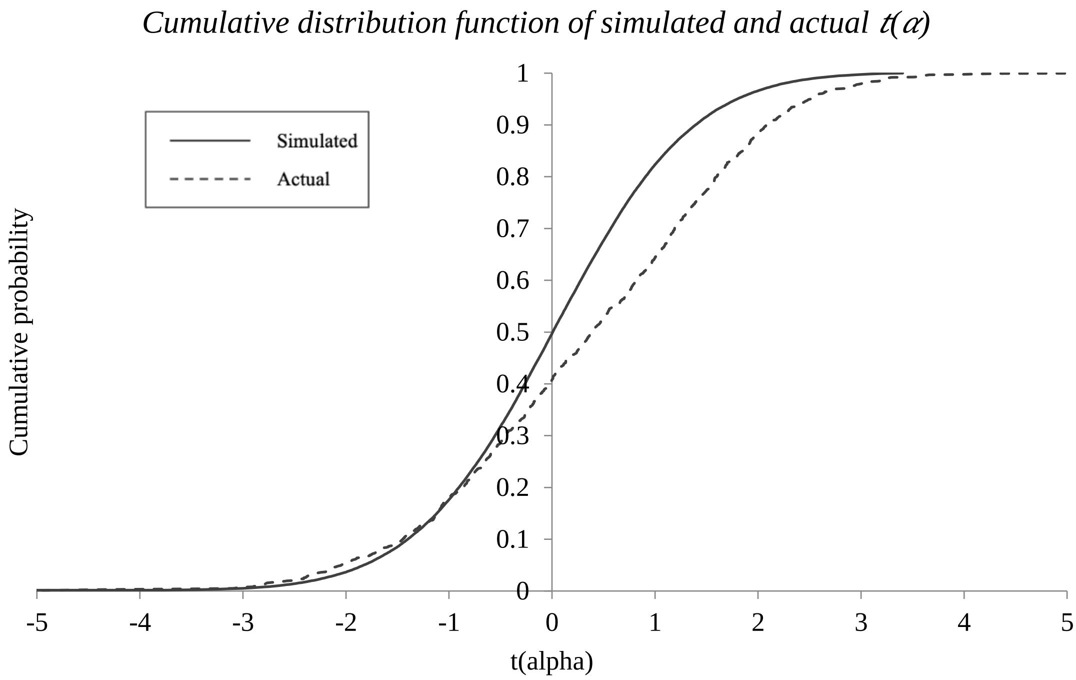


Figure 2. Cumulative distribution function of actual and simulated t(α) for the entire cross-section of mutual funds (net returns).

In Table 4, we present the results of the formal test for the proportion of funds performing better than expected by pure chance. The rightmost column displays the percentage of simulated values (luck distribution) that are lower than the actual value (actual distribution of fund managers). The t(α) values at the 1st, 5th and 10th percentiles of the actual distribution are lower than their respective average simulated values. For instance, at the 5th percentile, only 23.2% of the simulated values are below the actual value. This implies that in 76.8% of all cases, relying solely on pure bad luck would lead to better results than those achieved by actual managers.

To determine which levels of performance are likely due to luck alone and which can be attributed to skill, we follow the approach of Fama and French (2010). Rather than conducting t-tests or z-tests on the data, which would impose certain distribution characteristics on the luck distribution, we examine how many simulated values are below or above the actual value for a given percentile. Following Fama and French, we ascertain that if the actual value is smaller than 20% of the simulated values, the performance is likely due to negative skill. Similarly, when the percentage of actual values surpassing simulated values is greater than 80%, the performance is most likely attributed to skill. In the subsequent discussion, we refer to this decision rule as the "20%-rule". More stringent versions of this rule could dictate that managers are considered skilled only if they surpass 90% or 95% of the simulated values, but these fall beyond the scope of our analysis.

The outcomes in Table 4 indicate that this threshold is exceeded, starting from the 40th percentile of the actual distribution. At this juncture, as per the "20%-rule", the observed distribution of outperformance can be attributed to skill rather than luck. As we move further to the right of the distribution (toward higher percentiles), the proportion of simulated values below their corresponding actual values continues to rise. This trend suggests that it is becoming increasingly likely that the outperformance was generated by skill. However, at the 70th percentile, the maximum proportion of 98.2% is attained, beyond which there is a slight declining trend until the 99th percentile of the distribution.

Table 4. Percentiles of $t(\alpha)$ estimates for simulated and actual actively managed mutual fund returns, July 2001–July 2021 (net returns).

Percentiles of $t(\alpha)$ estimates for the entire cross-section (net returns)			
Percentiles	Actual	Simulated	% (Simulated < Actual)
1	−2.85	−2.63	28.3%
5	−2.04	−1.79	23.0%
10	−1.44	−1.37	38.3%
20	−0.86	−0.88	52.2%
30	−0.45	−0.53	62.0%
40	−0.02	−0.26	80.2%
50	0.40	0.00	91.8%
60	0.82	0.29	97.7%
70	1.19	0.57	98.2%
80	1.60	0.91	98.2%
90	2.09	1.36	97.7%
95	2.51	1.74	97.4%
97	2.80	2.05	97.8%
99	3.24	2.48	96.0%

Note(s): The leftmost column of the table shows the respective percentile. The column next to it, "Actual", shows the percentiles of $t(\alpha)$ estimates of the actual cross-section. The "Simulated" column shows the average of all 10,000 percentiles of t(α) estimates of the different iterations of the bootstrap simulation. The rightmost column depicts the percentages of simulated values that are below the actual value.

In summary, a significant portion of mutual funds' performance in the cross-section (approximately 60%) display a positive alpha, while the remaining 40% aligns with a luck distribution. This implies that a majority of funds perform better than what luck alone would indicate. As a result, hypothesis 1 finds support from the data. To provide a context within a developed market, we undertake a similar analysis for the US market. The corresponding outcomes are detailed in Internet Appendix Table A.1, revealing that the 80% threshold is not surpassed for any percentile below the 97th. This observation closely mirrors that of Fama and French (2010), confirming the perspective that a substantial portion of US mutual fund returns are influenced by luck rather than skill.

Regarding hypothesis 1, we also conducted sensitivity analysis. Initially, we applied a distinct set of factor portfolios by directly using emerging market factors from French's homepage (note that this collection of factor portfolios encompasses more countries than the Chinese stock market). The outcome still supports the conclusion that a majority of Chinese mutual funds seems to deliver positive risk-adjusted alphas (refer to Table A.2 in the Internet Appendix). Second, we confined the sample period to the duration utilized by Yang and Lui (2017). During this timeframe, Yang and Lui didn't find substantial evidence for skill within the cross-section of Chinese mutual fund managers. We have gathered the statistics for the corresponding sample period, which underpins the notion that a positive alpha is primarily observed in more recent years (see Appendix Table A.3). Third, we present the outcomes of gross returns (obtained by reintroducing 1/12 of the funds' annual expenses to the monthly returns) in Table A.4. The threshold of 80% is initially surpassed at the 20th percentile, suggesting that between the 20th and 40th percentile, some level of skill is evident before accounting for management fees. However, this level of skill falls short of covering those fees.

Subsequently, we employ the injected alpha method. Following the approach of Fama and French (2010), we increment the standard deviation (σ) in steps of 0.25%, ranging from 0.25% to 2%. To determine the appropriate standard deviation that encompasses the left and right tails of the distribution, we again invoke Fama and French's "20% rule". This entails selecting the σ value at which the percentage of simulated values below the actual value becomes less than 80% for the right tail and exceeds 20% for the left tail.[6]

We concentrate on the 99th percentile (last row of Table 5). At the value of 1.5%, the injected distribution aligns with the actual distribution for the first time, in line with the 20% rule. This outcome reinforces the substantial outperformance of the active managers compared to the passive benchmark as observed in the bootstrap analysis.

In summary, the analysis of hypothesis 1 suggests that the alpha and corresponding t-values in the cross-section of Chinese fund managers are not consistent with pure luck. Rather, about 60% of all fund managers appear to possess skills that translate, according to the injected alpha method, into an alpha from Equation (1) of approximately 1.5% per annum. The level of alphas evident in the Chinese

[6] In line with Fama and French (2010), it is anticipated that there is a 20% probability of setting the lower bound to be low and conversely a 20% probability of setting the upper bound to be high. This corresponds to a 0.5% bound around the σ value that encompasses either tail. To conserve space, we refrain from presenting this procedural boundary.

fund market is notably larger than that observed in more developed markets, such as the US (Fama and French, 2010; Cuthbertson and Nitzsche, 2013).

Table 5. Percentiles of $\mathbf{t(\alpha)}$ estimates for simulated and actual actively managed mutual fund returns with injected alpha (net returns).

Percentage of simulated values below the actual value										
Percentile	Actual $t(\alpha)$	$\sigma = 0$	0.25	0.5	0.75	1	1.25	1.5	1.75	2
1	−2.85	28.3%	31.2%	33.4%	40.0%	47.6%	56.6%	72.7%	83.2%	91.9%
5	−2.04	23.0%	26.7%	25.4%	30.2%	34.8%	40.1%	50.4%	58.7%	68.8%
10	−1.44	38.3%	41.5%	42.7%	46.1%	51.1%	54.1%	61.7%	68.1%	73.9%
20	−0.86	52.2%	54.8%	56.8%	55.8%	60.7%	62.2%	67.2%	70.8%	74.8%
30	−0.45	62.0%	63.3%	66.2%	66.0%	68.3%	68.9%	72.2%	73.5%	76.1%
40	−0.02	80.2%	80.3%	83.1%	82.3%	84.5%	83.9%	85.2%	84.1%	84.6%
50	0.40	91.8%	91.9%	93.0%	92.7%	93.6%	93.0%	93.9%	92.6%	92.0%
60	0.82	97.7%	97.7%	97.7%	98.0%	97.7%	97.3%	98.7%	96.5%	96.9%
70	1.19	98.2%	98.3%	98.0%	98.3%	98.1%	97.9%	98.7%	96.8%	96.8%
80	1.60	98.2%	98.2%	98.5%	99.1%	98.4%	98.2%	98.4%	96.6%	96.1%
90	2.09	97.7%	96.6%	97.1%	97.6%	96.6%	95.8%	94.5%	93.2%	89.2%
95	2.51	97.4%	96.1%	96.1%	95.7%	94.9%	94.3%	92.1%	86.8%	81.9%
97	2.80	97.8%	96.2%	95.9%	95.3%	94.4%	92.1%	89.3%	82.6%	74.9%
99	3.24	96.0%	94.2%	93.7%	92.9%	89.9%	83.2%	75.3%	59.3%	44.2%

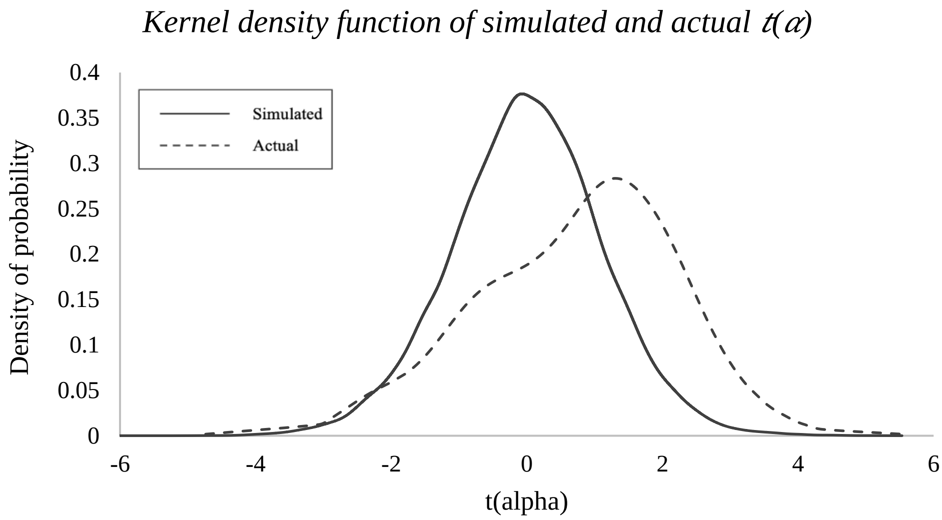
Note(s): The leftmost column shows the respective percentile, and the next column, "Actual", shows the percentiles of $t(\alpha)$ estimates of the actual cross-section. The columns to the right depict the average of all 10,000 percentiles of $t(\alpha)$ estimates of the different iterations of the bootstrap simulation to which an injected alpha with the respective sigma has been added.

4.3.2. Local versus foreign fund managers (hypothesis 2)

In the last section, we demonstrated that the actual distribution of skill exhibits two humps (refer to Figure 1). As we formulated our hypotheses, we postulated that this pattern could potentially be clarified by information asymmetry between local and foreign fund managers. We proceed to investigate hypothesis 2: Local fund managers exhibit a higher level of alpha compared to foreign managers. Our emphasis is on graphical analysis, while comprehensive statistical test details are available in the Internet Appendix. In Section 5, we encapsulate the injected alpha method employed to test this hypothesis as well as the subsequent ones.

To begin, we bifurcated the mutual funds cross-section into subsets managed by local and foreign managers, respectively. Subsequently, we engaged in a comparison between the kernel density functions of the simulated and actual distributions, as depicted in Figure 3. In Panel A, the graphical representation showcases the simulated and actual distributions for local managers. Analogous to the complete sample, a majority of these managers surpass expectations derived from luck. Notably, the prowess of local managers appears particularly striking, with the dashed line situated significantly to the right of the simulated line across much of the graph. On the left side of the distribution, we once again observe a minority of fund managers whose performance falls below the level one might expect from mere bad luck; however, this proportion is smaller compared to the entire sample.

Panel A: Local fund managers



Panel B: Foreign fund managers

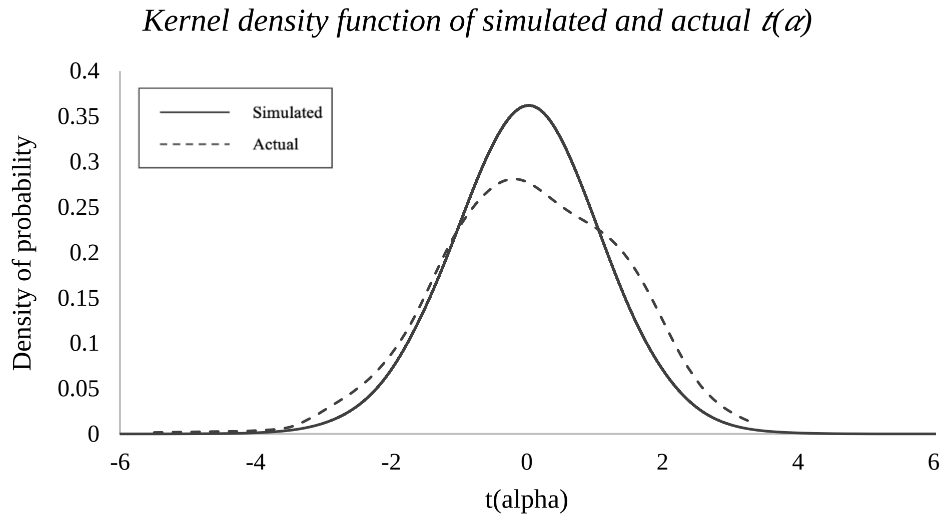


Figure 3. Kernel density function of simulated and actual $\mathbf{t(\alpha)}$ for local versus foreign cross-section of mutual funds (net returns).

Panel B portrays the actual and simulated distributions for foreign managers, revealing a distinct perspective on skill. The two distributions display a closer alignment, suggesting that foreign fund managers possess comparatively less skill than their local counterparts. Although it is evident that a segment of foreign managers surpasses luck-derived expectations, the proportion exhibiting positive alphas is notably smaller than among local managers. Concurrently, the segment of foreign managers underperforming what luck would predict is more pronounced than that of local managers. In summary, the two peaks observed in the overall sample's actual distribution (refer to Figure 1) have nearly vanished in the individual subsamples; the overlapping peaks of the local and foreign distributions coincide with and elucidate the pair of peaks detected in the complete sample.[7]

By applying the "20% rule", the local fund manager group surpasses this threshold at the 20th percentile, while foreign fund managers only achieve it at the 80th percentile (for further details, see Internet Appendix A.5). In simpler terms, 80% of local managers display performance that cannot be attributed solely to luck (indicating skill), whereas only 20% of foreign managers deliver alphas surpassing luck-derived expectations. This numerical comparison furnishes robust evidence supporting the hypothesis that local managers perform better than their foreign counterparts, in line with the conclusions drawn by Wagner and Margaritis (2017).

To gain further insights into the asymmetry explanation, we examine the findings of Mondria et al. (2021). They propose that "information asymmetries between locals and non-locals are more pronounced when it comes to good news, with information regarding bad news being relatively symmetric" (p. 1). Therefore, we segment our sample into four distinct five-year subperiods (refer to Table 6), wherein the first and third subperiods correspond to unfavorable news phases, exhibiting a negative Sharpe ratio and an average return close to zero (using the Chinese Total Market Index from Datastream). Conversely, the second and fourth subperiods represent favorable information environments, with average returns of approximately 10% p.a. Consequently, the Sharpe ratio during these latter periods significantly surpasses that of the two former ones. If Mondria et al.'s (2021) assertion holds true, information asymmetries should intensify during subperiods characterized by higher Sharpe ratios (namely, the second and fourth subperiods). As a consequence, disparities in performance measures between foreign and Chinese fund managers should be more pronounced during prosperous market phases.

Table 6. Percentiles of $\mathbf{t(\alpha)}$ estimates for simulated and actual actively managed small-cap mutual fund returns from July 2001 to July 2021 (net returns).

Five years subperiods	Average return	Standard deviation	Sharpe ratio
200107–200606	−2.73%	21.19%	−21.11%
200607–201106	10.84%	41.17%	20.92%
201107–201606	1.84%	26.59%	−1.89%
201607–202107	9.79%	17.08%	50.86%

The outcomes of the simulated alpha distribution, as presented in Figure 4, closely align with the information asymmetry theory put forth by Mondria et al. (2021). During the first and third periods featuring negative Sharpe ratios, the distribution of alphas appears similar between foreign and Chinese fund managers. In contrast, the second and fourth subperiods, marked by higher average returns and elevated Sharpe ratios, unveil a more pronounced prevalence of positive alphas among Chinese fund managers compared to their foreign counterparts. Hence, the subperiod analysis lends

[7] We also analyzed whether a momentum factor potentially explains the results. Therefore, we repeated the analysis using the six-factor model of Fama and French (2018) and found similar results, see Figure A.1 in the Internet Appendix.

additional support to the notion that disparities in alphas stem from information asymmetries. Furthermore, even the final subperiod—where both local and foreign fund managers display a certain degree of skill—maintains consistency with the information asymmetry argument. This outcome can be rationalized by the dominance of retail investors, who possess lower skill levels, in the trading activity of the Chinese stock market (as evidenced by Chen and Wu, 2022). Consequently, the result of this subperiod implies that both groups of mutual fund managers are able to capitalize on the activities of less skilled retail investors.

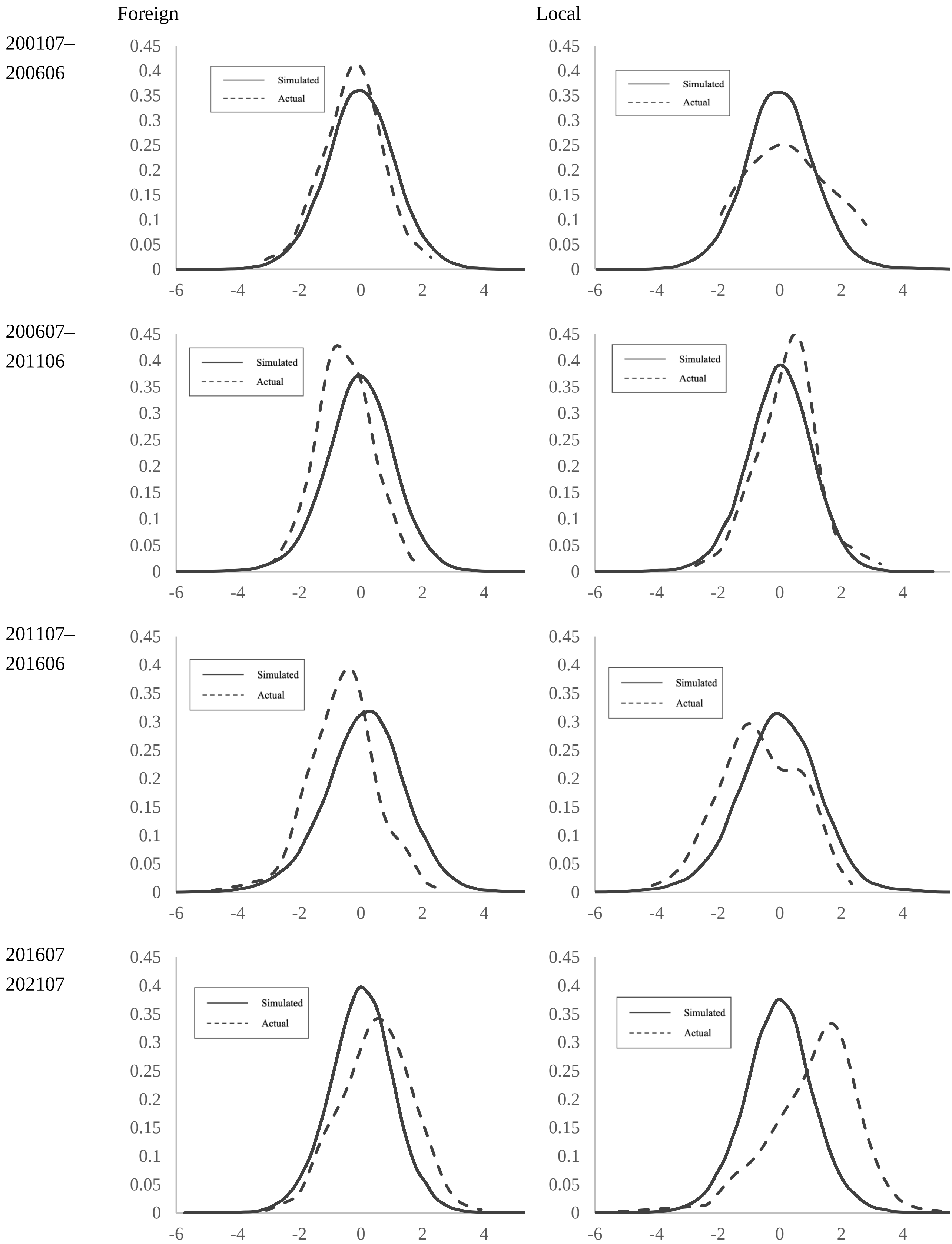


Figure 4. Kernel density function of simulated and actual $\mathbf{t}(\boldsymbol{\alpha})$ for local versus foreign cross-section of mutual funds (net returns).

4.3.3. Small- and mid-cap versus large-cap fund managers (hypothesis 3)

Indeed, we have put forth the argument that the influence of information asymmetry between local and foreign managers should be more pronounced in the small- and mid-cap stocks market segment compared to the impact on large-cap stocks. Consequently, this section delves into the assessment of the associated hypothesis, namely hypothesis 3: A larger proportion of local small- and mid-cap fund managers exhibit positive alphas in comparison to their foreign counterparts managing similar funds.

Certainly, Figure 5 provides a graphical representation of the distribution functions for all four potential combinations. The upper two graphs are dedicated to the performance of local and foreign managers handling small- and mid-cap funds, while the lower two graphs pertain to the same groups managing large-cap funds. A couple of key findings emerge from these graphs.

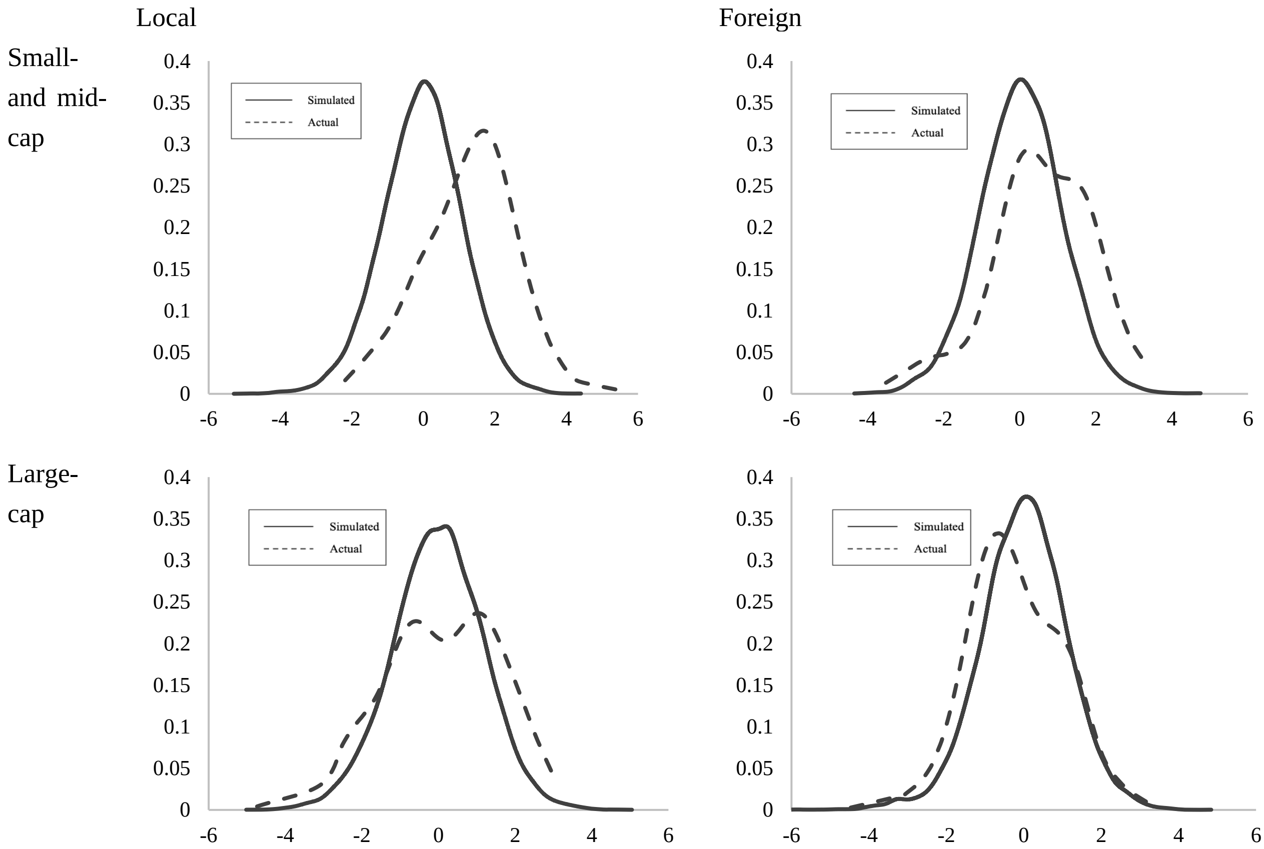


Figure 5. Kernel density function of simulated and actual t(α) for local versus foreign cross-section of mutual funds (net returns). Note(s): On the y-axis of each graph, the density of probability is plotted, while t(α) values are plotted on the x-axis.

First, for both local and foreign managers, those overseeing small- and mid-cap funds demonstrate better results compared to their counterparts managing large-cap funds. Second, among managers handling small-, mid- and large-cap funds, the local managers tend to outperform their foreign counterparts. These findings strongly align with our information asymmetry proposition, specifically highlighting that the most pronounced demonstration of skill lies within the subset of local managers focusing on small- and mid-cap funds. From a visual perspective, there is no instance within this group where a manager performs worse than what pure chance would predict. Conversely, a significant majority of these managers exhibit superior performance beyond what random sampling would anticipate. While a similar pattern is observed among foreign small- and mid-cap managers, their outperformance is relatively less marked. Notably, there exists a small portion of foreign managers who perform worse than what chance would suggest.

Among local managers of large-cap funds, performance appears to be explicable solely by chance, even though there is a minor segment of managers whose performance lies below expectations (left tail) and another minority whose performance surpasses expectations (right tail). Conversely, the subset with the poorest performance consists of foreign managers overseeing large-cap funds. Visually, it appears that none of the managers in this category outperform what chance would predict. On the flip side, a substantial portion within this group actually underperforms compared to a luck-based expectation.

The outcomes, as described visually above, are corroborated by the numerical findings when applied to small-, mid- and large-cap managers (further details are summarized in Table A.6 in the Internet Appendix). For local fund managers, every individual within the subset of small- and mid-cap managers outperforms what chance would predict. This holds true even at the 1st percentile of the actual distribution, where performance is better than 89.5% of all simulated outcomes. In contrast, for local large-cap managers, the 20%-rule is applicable within the 60th and 97th percentile, encompassing only 37% of all local managers. In other words, roughly a third of local large-cap managers fare better than what luck would anticipate, while the entirety of local small- and mid-cap managers demonstrate skill.

Slightly less pronounced but still notable is the case for foreign managers. Within this category, 80% of small- and mid-cap managers outperform what random sampling would predict. However, none of the foreign large-cap managers appear to exhibit skill. In summary, both the graphical and numerical findings align with the notion that small- and mid-cap managers display a greater degree of skill compared to their large-cap counterparts. Furthermore, local small- and mid-cap managers demonstrate significantly higher alphas than their foreign counterparts, while the difference among large-cap managers is less distinct.

4.3.4. Value versus growth fund managers (hypothesis 4)

Last, we test hypothesis 4: Local value managers show a larger share of positive alphas than foreign managers. We suspect that information asymmetries are larger in the value domain than for growth stocks since the valuation of a company requires in-depth knowledge of the Chinese accounting system. However, forecasting the growth of company cash-flows is more difficult (e.g., Cochrane, 2011). Therefore, we expect that information asymmetries may have a more substantial effect for value stocks than for growth stocks and that this effect will be greater for local than foreign fund managers.

Figure 6 reflects all possible combinations of actual and simulated alpha distributions with respect to value or growth stocks and local or foreign fund managers. The subsample exhibiting the most compelling case for positive alphas is that of local value-fund managers. No manager in this subsample seems to perform worse than bad luck would suggest, while the majority performs better. In contrast, foreign value managers perform roughly in line with what random sampling would suggest. However, there is a small minority that performs worse than luck would suggest. These observations provide some support for hypothesis 4. Additionally, alpha differences between local and foreign managers are larger in the value domain than in growth stocks. However, managers focusing on growth companies generate performance largely consistent with luck.

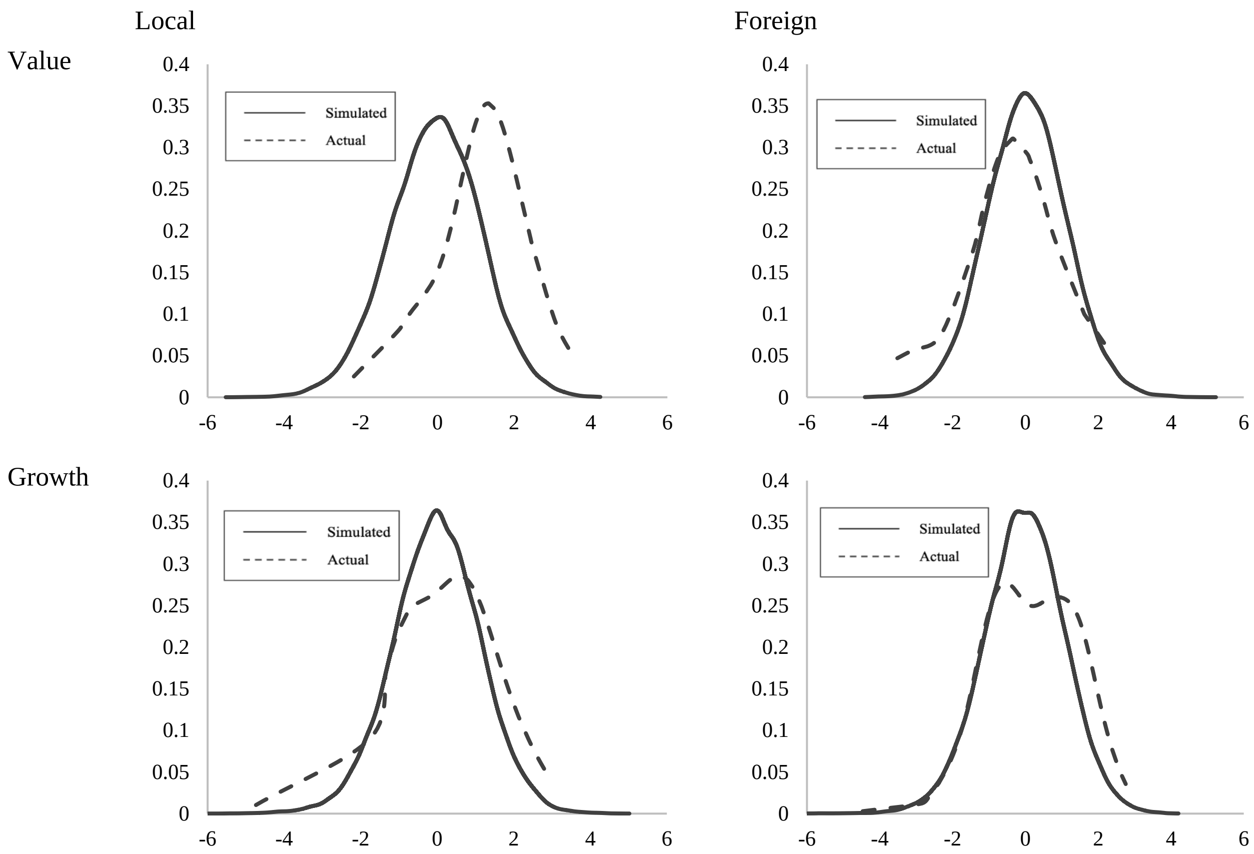


Figure 6. Kernel density function of simulated and actual $t(\alpha)$ for local and foreign mutual fund cross-sections (net returns). Note(s): The density of probability is plotted on the y-axis of each graph; $t(\alpha)$values are plotted on the x-axis.

The numerical results presented in Table A.7 of the Internet Appendix support the graphical observations. Among local value managers, a sizeable majority — 95% (from the 5th to the 99th percentile) — outperform the randomly sampled distribution in accordance with the 20% rule; there are no managers who fare worse than bad luck would suggest. In contrast, there is no outperformance by foreign value managers that cannot be explained by luck. On the left side of the tail, the 1st, 5th and 10th percentiles all fare worse than bad luck would suggest. These statistics provide strong additional support for hypothesis 4. In sum, the entire group of value managers seems to deliver a higher level of alphas than growth managers, and local managers are particularly skillful compared with their foreign counterparts in the value domain.

5. Discussion

The results examined above are further supported by the data in Table 7, where the injected alpha captures the right tail of the actual distribution according to the 20% rule (Fama and French, 2010). Our analysis shows that the level of risk-adjusted alpha observed among all fund managers in the cross-section is inherent only for certain groups of managers and investment styles. First, the group of local managers delivers more alpha than their foreign counterparts. Second, among small- and mid-cap and value managers, the difference in alpha is even more pronounced than among managers of growth and large-cap funds. These results quantify the potential level of alpha evident in the comparison of the actual and simulated luck distribution in the preceding section. The injected alpha method suggests that local fund managers are able to deliver an annualized alpha of about 2% across all investment styles, while the alpha of foreign managers is only about 0.25% per annum.

In the small- and medium-cap and value domain, the performance is substantially higher for local Chinese fund managers. Foreign fund managers seem to deliver a positive alpha only for those following a small- and medium-cap investment style. If we compare the results with the style analysis of Wagner and Margaritis (2017) for emerging markets in general, we find similarities but also differences. In emerging markets, Wagner and Margaritis also found a higher return for local fund managers compared to foreign ones. The reported return difference of 1.8% p.a. after fees is close to that reported in Table 7. However, the positive alphas in the small- and medium-cap domain and value domain are not observed for the emerging market sample used by Wagner and Margaritis. Thus, the Chinese fund market may be different from the average emerging market country, which is obvious since emerging countries are generally diverse. Also, their analysis covers an earlier sample period (1996–2010) and uses the Carhart (1997) regression methodology; therefore, results are not directly comparable.

Table 7. Injected alpha mutual fund returns, July 2001–July 2021 (net returns).

Fund	All	Local	Foreign
All	1.50%	2.00%	0.25%
Small- and medium-cap	2.75%	4.00%	2.00%
Large-cap	0.00%	0.00%	0.00%
Value	1.75%	2.50%	0.00%
Growth	0.00%	0.50%	0.00%

Note(s): The table shows the respective alpha, at which the end of the right tail of the actual $t(\alpha)$ was captured by the simulated distribution according to the 20% rule introduced by Fama and French (2010).

These observations have important implications. First, a significant majority of Chinese managers exhibit performance better than luck would suggest over the sample period. These results stand in stark contrast to those of similar studies focused on developed markets, suggesting that there are factors influencing the market that allow some managers to generate positive alphas. When formulating hypothesis 2, we considered the possibility of an alpha difference between local and foreign managers resulting from an information asymmetry between them. The results of using the bootstrap and injected alpha methods to test hypothesis 2 align with the explanation of information asymmetry; local managers delivered much better performance than their foreign counterparts. The subsample analysis further suggests that the information advantage held by Chinese managers is particularly pronounced in a positive market environment. This observation is consistent with the information asymmetry hypothesis of Mondria et al. (2021).

To further analyze the asymmetry explanation, we formulated and tested hypotheses 3 and 4. If the performance disparity between foreign and local managers resulted from information barriers, one would anticipate local managers of small- and mid-cap as well as value funds to outperform their foreign counterparts to a greater extent than in large-cap and growth stocks. The information asymmetries in the former segments would have a more significant effect on the stock's performance. The rationale for this is rooted in the prerequisites for success in such investment strategies. The disparity between local and foreign managers is evident among small- and mid-cap managers. Smaller companies typically receive less coverage from analysts, making it challenging to find reliable information about them. Information barriers are likely to impact local small- and mid-cap managers to a lesser degree than their foreign counterparts, giving them an information advantage in accessing companies and identifying inefficiencies more swiftly. As a result, they generate superior returns.

Similar arguments apply to value-fund managers. Accurate familiarity with local accounting practices and dependable access to accounting data are necessary to identify undervalued companies. These information asymmetries could contribute to local value managers possessing the information needed to identify undervalued stocks, leading to higher returns compared to their foreign counterparts. In the context of fund returns, this indicates that Chinese fund managers demonstrate a positive performance surpassing what would be expected from pure luck.

On the other hand, the performance gap among large-cap and growth managers is expected to be less pronounced, given that the information needed for identifying growth prospects and assessing larger companies is more widely accessible to all participants in the market. As previously mentioned, the outcomes derived from both the bootstrap and injected alpha analyses align with our anticipated outcomes within the framework of information asymmetry.

Based on our analysis, we conclude that the substantial alphas observed in the entire cross-section of mutual funds from July 2001 to July 2021 is primarily attributed to local managers who concentrate on small- and mid-cap stocks and value strategies. This can be attributed to the better access to superior information possessed by these local managers in comparison to their foreign counterparts.

6. Conclusions

Following Fama and French (2010), we employed a bootstrap method to analyze 1,221 Chinese mutual funds active from July 2001 to July 2021. In contrast to previous studies focused on developed markets, such as Europe or the US, this study indicates that the majority of active managers in China earned alphas that were large enough to cover their costs. The injected alpha method revealed that the true annualized alpha at the right tail of the distribution of net returns lies around 1.5%.

The second part of the analysis provided an explanation for the observed alpha. We contend that there exists an information asymmetry between foreign and local managers, which accounts for why specific groups of managers within the cross-section deliver a higher alpha than others. Building on this reasoning, we formulated three additional hypotheses. To begin, we subdivided the entire cross-section into local and foreign managers for further examination. The outcomes corroborate the hypothesis that local fund managers yield a higher alpha compared to their foreign counterparts. We estimated the sigma of the injected alphas to be 2% per annum for Chinese fund managers and merely 0.5% for foreign managers.

Subsequently, we delved deeper into the cross-section by segmenting the local and foreign manager groups into those concentrating on small- and mid-cap companies and those concentrating on large-cap companies. Additionally, both local and foreign managers were categorized into value and growth managers. The outperformance was primarily observed among managers adhering to a small- and mid-cap value investment approach. Within each style, local asset managers generated a higher alpha than their foreign counterparts (4% versus 2% for small- and mid-caps and 2.5% versus 0% for value stocks). Derived from these findings, we ascertain substantial evidence that access to information constitutes a pivotal factor explaining a manager's alpha.

The results of this study hold great practical significance for investment management not only in China but also in other regions. Investors aiming to enhance their exposure to Chinese small- and mid-cap or value strategies should opt for a local manager, as they are more likely to outperform their counterparts. Conversely, foreign investment managers should focus on enhancing their access to market information in order to enhance their performance.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Agyei-Ampomah S, Clare A, Mason A, et al. (2015) On luck versus skill when performance benchmarks are style-consistent. *J Bank Financ* 59: 127–145. https://doi.org/10.1016/j.jbankfin.2015.05.013

Ayers BC, Ramalingegowda S, Yeung PE (2011) Hometown advantage: The effects of monitoring institution location on financial reporting discretion. *J Account Econ* 52: 41–61. https://doi.org/10.1016/j.jacceco.2011.03.003

Berk J, van Binsbergen JH (2015) Measuring skill in the mutual fund industry. *J Financ Econ* 118: 1–20. https://doi.org/10.1016/j.jfineco.2015.05.002

Blake D, Caulfield T, Ioannidis C, et al. (2017) New evidence on mutual fund performance: a comparison of alternative bootstrap methods. *J Financial Quant Anal* 52: 1279–1299. https://doi.org/10.1017/S0022109017000229

Carhart MM (1997) On persistence in mutual fund performance. *The Journal of Finance* 52: 57–82. https://doi.org/10.2307/2329556

Chan K, Covrig V, Ng L (2005) What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. *J Finance* 60: 1495–1534. https://doi.org/10.1111/j.1540-6261.2005.768_1.x

Chen X, Wu C (2022) Retail investor attention and asymmetry: evidence from China. *Pacific-Basin Finance J* 75: 1–19. https://doi.org/10.1016/j.pacfin.2022.101847

Chung CY, Sul HK, Wang K (2021) A tale of two forms of proximity: Geography and market. *J Bus Res* 122: 14–23. https://doi.org/10.1016/j.jbusres.2020.08.060

Cuthbertson K, Nitzsche D (2013) Performance, stock selection and market timing of the German equity mutual fund industry. *J Empir Finance* 21: 86–101. https://doi.org/10.1016/j.jempfin.2012.12.002

Cochrane JH (2011) Presidential address: Discount rates. *J Finance* 66: 1047–1108. https://doi.org/10.1111/j.1540-6261.2011.01671.x

Corbet S, Hou Y, Hu Y, et al. (2020) The influence of the COVID-19 pandemic on asset-price discovery: Testing the case of Chinese informational asymmetry. *Int Rev Financial Anal* 72: 1015–1060. https://doi.org/10.1016/j.irfa.2020.101560

Cornell B, Hsu J, Kiefer P, et al. (2020) Assessing mutual fund performance in China. *J Portf Manag* 46: 118–127. https://doi.org/10.3905/jpm.2020.1.140

Deng Y, Xu Y (2014) Do institutional investors have superior stock selection ability in China? *China J Account Res* 4: 107–119. https://doi.org/10.1016/j.cjar.2011.06.001

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J Financ Econ* 33: 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama EF, French KR (2010) Luck versus skill in the cross-section of mutual fund returns. *J Finance* 65 : 1915–1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

Fama EF, French KR (2015) A five-factor asset pricing model. *J Financ Econ* 116: 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama EF, French KR (2018) Choosing factors. *J Financ Econ* 128: 234–252. https://doi.org/10.1016/j.jfineco.2018.02.012

Ferreira MA, Matos P, Pereira JP, et al. (2017) Do locals know better? A comparison of the performance of local and foreign institutional investors. *J Bank Financ* 82: 1–164. https://doi.org/10.1016/j.jbankfin.2017.06.002

Fifield SG, Jetty J (008) Further evidence on the efficiency of the Chinese stock markets: A note. *Res Int Bus Finance* 22: 351–361. https://doi.org/10.1016/j.ribaf.2008.02.002

Gao J, O'Sullivan N, Sherman M (2020) An evaluation of Chinese securities investment fund performance. *Q Rev Econ Finance* 76: 249–259. https://doi.org/10.1016/j.qref.2019.08.007

Gao J, O'Sullivan N, Sherman M (2021) Chinese securities investment funds: The role of luck in performance. *Rev Account Financ* 20: 271–297. https://doi.org/10.1108/RAF-07-2020-0182

Grinblatt M, Keloharju M (2000) The investment behavior and performance of various investor types: A study of Finland unique data set. *J Financ Econ* 55: 43–67. https://doi.org/10.1016/S0304-405X(99)00044-6

Harvey CH, Liu Y (2020) False (and missed) discoveries in financial economics. *J Finance* 75: 2503–2553. https://doi.org/10.1111/jofi.12951

Jensen MC (1968) The performance of mutual funds in the period 1945–1964. *J Finance* 23: 389–416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Kiymaz H (2015) A performance evaluation of Chinese mutual funds. *In J Emer Mark* 10: 820–836. https://doi.org/10.1108/IJoEM-09-2014-0136

Kosowski R, Timmermann A, Wermers R, et al. (2006) Can mutual fund "stars" really pick stocks? New evidence from a bootstrap analysis. *J Finance* 61: 2551–2595. https://doi.org/10.1111/j.1540-6261.2006.01015.x

Koutmos D, Wu B, Zhang Q (2020) In search of winning mutual funds in the Chinese stock market. *Rev Quant Finance Account* 54: 589–616. https://doi.org/10.1007/s11156-019-00800-z

Kutan AM, Lin H, Sun PW, et al. (2018) A reliable performance measure to differentiate China's actively managed open-end equity mutual funds. *Appl Econ* 50: 5592–5603. https://doi.org/10.1080/00036846.2018.1488055

Leuz C, Lins KV, Warnock FE (2008) Do foreigners invest less in poorly governed firms? *Rev Financ Stud* 22: 3245–3285. https://doi.org/10.1093/rfs/hhn089

Li S, Brockman P, Zurbruegg R (2015) Cross-listing, firm-specific information, and corporate governance: Evidence from Chinese A-shares and H-shares. *J Corp Finance* 32: 347–362. https://doi.org/10.1016/j.jcorpfin.2014.10.008

Li Y, Yan D, Greco J (2006) Market segmentation and price differentials between A shares and H shares in the Chinese stock markets. *J Multinatl Financial Manag* 16: 232–248. https://doi.org/10.1016/j.mulfin.2005.07.003

Liang Q, Liao J, Leng L (2021) Social interactions and mutual fund portfolios: The role of alumni networks in China. *China Financ Rev Int* 12: 433–450. https://doi.org/10.1108/CFRI-04-2021-0073

Malloy C (2005) The geography of equity analysis. *J Finance* 60: 719–755. https://doi.org/10.1111/j.1540-6261.2005.00744.x

Mondria J, Wang X, Wu T (2021) Familiarity and surprises in international financial markets: bad news travel like wildfire, good news travels slow. *J Int Money Finance* 115: 1–16. https://doi.org/10.1016/j.jimonfin.2021.102390

MSCI (2021) MSCI China All Shares Index (USD) Factsheet (July).

Parshakov P (2014) Russian Mutual Funds: Skill vs. Luck. https://dx.doi.org/10.2139/ssrn.2539490

Pilbeam K, Preston H (2019) An empirical investigation of the performance of Japanese mutual funds: Skill or luck? *Int J Financ Stud* 7: 6. https://doi.org/10.3390/ijfs7010006

Rao Z, Ahsan T, Tauni MZ, et al. (2018) Performance and persistence in performance of actively managed Chinese equity funds. *J Quant Econ* 16: 727–747. https://doi.org/10.1007/s40953-017-0104-5

Seddighi HR, Nian W (2004) The Chinese stock exchange market: operations and efficiency. *Appl Financial Econ* 14: 785–797. https://doi.org/10.1080/0960310042000180826

Suh S, Hong K (2011) Control of luck in measuring investment fund performance. *Asia-Pacific J Financ Stud* 40: 467–493. https://doi.org/10.1111/j.2041-6156.2011.01046.x

Titman S, Wei C, Zhao R (2021) Corporate actions and the manipulation of retail investors in China: an analysis of stock splits. *J Financ Econ* 145: 762–787. https://doi.org/10.1016/j.jfineco.2021.09.018

Wagner M, Margaritis D (2017) All about fun(ds) in emerging markets? The case of equity mutual funds. *Emerg Mark Rev* 22: 62–78. https://doi.org/10.1016/j.ememar.2017.08.004

Yang L, Liu W (2017) Luck versus skill: Can Chinese funds beat the market? *Emerg Mark Finance and Trade* 53: 629–643. https://doi.org/10.1080/1540496X.2015.1097951