Queensland University of Technology
Brisbane Australia

This may be the author's version of a work that was submitted/accepted for publication in the following source:

Chen, Rui, Gao, Zhennan, Zhang, Xueyong, & Zhu, Min
(2018)
Mutual fund managers' prior work experience and their investment skills.
Financial Management, *47*(1), pp. 3-24.

This file was downloaded from: https://eprints.qut.edu.au/222986/

© Consult author(s) regarding copyright matters

This work is covered by copyright. Unless the document is being made available under a Creative Commons Licence, you must assume that re-use is limited to personal use and that permission from the copyright owner must be obtained for all other uses. If the document is available under a Creative Commons License (or other specified license) then refer to the Licence for details of permitted re-use. It is a condition of access that users recognise and abide by the legal requirements associated with these rights. If you believe that this work infringes copyright please provide details by email to qut.copyright@qut.edu.au

Notice: *Please note that this document may not be the Version of Record (i.e. published version) of the work. Author manuscript versions (as Submitted for peer review or as Accepted for publication after peer review) can be identified by an absence of publisher branding and/or typeset appearance. If there is any doubt, please refer to the published source.*

https://doi.org/10.1111/fima.12180

Accepted Article

Mutual Fund Managers' Prior Work Experience and Their Investment Skills

Rui Chen Zhennan Gao Xueyong Zhang Min Zhu[1]

February 2017

We are grateful to the Editor of this journal, Marc Lipson, and an anonymous referee. We thank discussants of workshop hosted by China Young Finance Scholars Society. Xueyong ZHANG acknowledges the financial support from National Natural Science Foundation of China (71673318, 71602198), program for innovation research and program for excellent academic talents of Central University of Finance and Economics. Rui CHEN acknowledges the financial support from National Natural Science Foundation of China (71403306), program for innovation research of Central University of Finance and Economics. All errors are our own.

[1] *Rui CHEN is an assistant professor in the School of Finance, Central University of Finance and Economics, Beijing, China. Zhennan GAO is a Ph.D. student in the School of Economics, Peking University, Beijing, China. Xueyong ZHANG, corresponding author, is a professor in the School of Finance, Central University of Finance and Economics, Beijing, China, Min ZHU is a lecturer in the Business School, Queensland University of Technology, Brisbane, QLD, Australia. Please corresponding to Prof. Xueyong Zhang, E-mail: zhangxueyong@cufe.edu.cn.*

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1111/fima.12180.

This article is protected by copyright. All rights reserved.

Accepted Article

Abstract

This paper examines the relationship between mutual fund managers' past professional backgrounds and their portfolio performance, using Chinese mutual fund data from 2003 to 2016. We focus on managers with prior work experience either as industry analysts or as macro analysts, the two most common career paths for Chinese fund managers. We hypothesize that managers who worked as industry analysts exhibit superior stock-picking skills, while managers with a background as macro analysts are more skillful in timing the market. These hypotheses are supported by the data, even after controlling for observable fund and manager characteristics. Bootstrap analyses suggest that the significant difference in performance between these two types of managers cannot be attributed purely to luck.

JEL classification: G11; G12; G19; G23; J24

Keywords: Managerial skills; stock-picking; market-timing; bootstrap

1. Introduction

An active manager can add value through deviating from her benchmark index in one of two ways: stock selection or market timing. Stock selection, or stock picking, places active bets on individual stocks (e.g., selecting underpriced stocks). Market timing involves dynamic betting on broad economic factors, such as overweighting particular sectors of the economy. Stock selection is a bottom-up approach, requiring thorough research on individual firms' business models and the value of their stock. Market timing, on the other hand, is a top-down approach to portfolio construction. Managers engaging in market timing presumably have a superior ability to process macroeconomic data so as to produce accurate

This article is protected by copyright. All rights reserved.

Accepted Article

forecasting. These two kinds of value-adding activities require different skill sets, and it is highly plausible that some fund managers excel in one skill more than the other.

Human capital is the stock of knowledge, habits, and social and personality attributes embodied in an individual's ability to produce economic value. The theory of human capital holds that greater human capital can transform into greater productivity. In mutual fund literature, a number of studies have investigated the effects of mutual fund managers' characteristics on their portfolio performance. Golec (1996) relates portfolio performance, risk, and fees to fund managers' characteristics, such as age, tenure, and education. Gottesman and Morey (2006) examine the influence of manager education, and conclude that education is a pertinent factor in performance. Cohen et al. (2008) show that fund managers with past educational ties to corporate board members outperform in the stocks of those corporations, suggesting that social networks can aid the transfer of private information. Sonney (2009) finds that European sell-side analysts with a country specialization outperform analysts with an industry specialization, indicating that an understanding of local product markets is crucial to analyzing stock valuation.

We believe that a fund manager's career path and training play an important role in the formation of human capital. Human capital, in turn, impacts the manager's portfolio strategies and styles. In particular, we focus on two types of professional background of mutual fund managers: industry analysts and macro analysts. *Industry analysts* are responsible for companies belonging to a certain industry sector, such as telecommunications or tourism, and possess a specialized knowledge of a large body of individual companies. In addition, as part of their investigations into individual firms, industry analysts build up close relationships with corporate managers in those firms. This detailed knowledge about individual companies and social connection with corporate managers give fund managers with a background as industry analysts the edge in processing firm-level information. Meanwhile, the primary mission of a *macro analyst* is to analyze and forecast government

This article is protected by copyright. All rights reserved.

Accepted Article

policy and macroeconomic trends affecting the market. A successful macro analyst is the one who has a greater understanding of overall risk factors and superior ability in forecasting macroeconomic trends. Close relationships with government officials developed over a period of years are also likely to contribute to the information advantage of managers who worked as macro analysts. All of these characteristics of a fund manager with a macro analyst background contribute to enhanced market-timing skills.

In this study, we hypothesize that fund managers with different professional backgrounds possess different investment skills. In particular, managers who worked as industry analysts have superior stock-picking skills, while managers who worked as macro analysts are better in timing the market. We test these hypotheses using a sample of Chinese mutual fund managers who had previously worked either as industry analysts or macro analysts.

Chinese mutual fund data provides us with several advantages. First, Chinese mutual funds are largely managed by solo managers: over 70% of funds are of single management currently.[2] This is opposite to the trend in the United States where team management has become the dominant management structure in its mutual fund industry. Studies by Wang (2016) and Patel and Sarkissian (2017) show that more than 70% of the U.S. domestic equity mutual funds have been team-managed in recent years. We are interested in the influence of fund managers' human capital on their investment skills on an individual level; therefore, Chinese mutual fund data serves our purpose well. Second, compared with a mature market such as the U.S. market, the Chinese market is quite volatile and experiences frequent sharp rises and falls, with a monthly stock market volatility reaching 9.65% compared with 4.45% on the S&P 500 between 1996 and 2015 (Chen, et al. 2016). This particular market

[2] Based on our calculation, the proportions of single-managed funds in Chinese mutual funds in recent years are 75% in 2012, 73% in 2013, 74% in 2014, and 69% in 2015.

This article is protected by copyright. All rights reserved.

Accepted Article

environment provides a level playing field for both stock pickers and market timers. In a market with low volatility, market timers are disadvantaged as their skills are not rewarded. As a result, the manager may appear to be unskilled for reasons unrelated to her actual skills. We show that this is not a concern for our study in a later section as both stock picking and market timing are equally rewarding in the Chinese market. Third, Chinese mutual fund data presents minimal survivorship bias. The Chinese mutual fund industry has enjoyed rapid growth in the past two decades, and it is rare a fund ceases operation.

Using the two classic modeling frameworks – Treynor and Mazuy (1966) and Henriksson and Merton (1981) – we decompose the abnormal fund returns into two parts: stock picking and market timing. To access the statistical significance of the investment skills, we apply a bootstrap analysis by Cao, et al. (2013). We find that managers with industry analyst experience exhibit superior stock-picking skills, presenting 0.40% or 0.46% higher alpha per month than the managers with macro analyst backgrounds in the Treynor-Mazuy model and Henriksson-Merton model, respectively. Meanwhile, managers who worked as macro analysts are better at timing markets, which is confirmed by their significant positive market-timing coefficients in the two abovementioned models. We conduct a wide array of robustness checks against possible alternative explanations, and our results hold in all these tests.

A recent study by Huang et al. (2015) has investigated the effects of prior work experience on the investment performance of Chinese fund managers. Our research, however, takes a different angle. Huang et al. (2015) focus on the relationship between prior work experience and concentration ratio of the portfolio and subsequent abnormal returns, but do not differentiate between the sources of the abnormal returns. Our study breaks down the investment skills into stock selection and market timing, and examines the impact of prior work experience on these two different skills separately. Existing literature has identified the fact that different subsets of managers excel in either stock picking or market timing, but

This article is protected by copyright. All rights reserved.

Accepted Article

factors that contribute to such skills remain largely unexplored. Our paper makes an initial attempt to identify the sources of these skills.

The paper is organized as follows. Section 2 describes our data of mutual funds and managers, as well as the models used to quantify investment skills. In Section 3, we analyze fund managers' stock-picking and market-timing skills. In particular, we focus on the connection between the past professional backgrounds of mutual fund managers and their investment performance. We employ the bootstrap analysis to eliminate the luck factor. In Section 4, we carry out more analysis to rule out alternative explanations for our results. Selection 5 reports robustness checks, and Section 6 concludes.

2. Data and Models

2.1 Chinese mutual funds and risk factors

The Chinese mutual fund industry has a short history, beginning in 1998. After a series of reforms, in September 2001, Hua An Chuang Xin -- the first open-ended mutual fund in China -- was founded. Since then the Chinese mutual fund industry has experienced exponential growth. There are 1,839 equity-oriented mutual funds (excluding index funds) in existence, with total assets of around $2.9 trillion Chinese Yuan, accounting for 4.27% of GDP (2016).[3] Hence, research on the Chinese mutual fund industry is meaningful and feasible.

The mutual fund monthly return data from January 2003 to December 2016 are drawn from the WIND database, a leading Chinese financial database and financial services provider. The fund returns are net of fees, and we only include equity-oriented funds that

[3] Data source: WIND database.

This article is protected by copyright. All rights reserved.

Accepted Article

invest in the Chinese market, which are identified by the categories provided in the WIND database. We exclude index funds in our sample, as their objective is to replicate a certain benchmark index rather than to engage in active management. We also remove team-managed funds as we focus on the impact of an individual fund manager's past professional background on investment skill.

The fund manager characteristics are sourced from the CSMAR database belonging to the GTA Finance and Education Group. The dataset contains information on managers' tenures, genders, and career paths. Chinese fund managers come from diverse career backgrounds including teaching, financial engineering, accountancy, civil service, industry analysis, and macro analysis. Of these, industry analyst and macro analyst are the two most common career backgrounds of Chinese fund managers, appearing in more than half of managers' résumés. The manager characteristics are merged with mutual fund performance data. We exclude managers with less than 24 monthly returns between January 2003 to December 2016. This process leaves us with 330 mutual fund managers who have the prior work experience as either industry analysts or macro analysts.[4] Out of these 330 fund managers, there are 258 who worked as industry analysts, and 72 who worked as macro analysts.

To standardize the performance of different fund managers regarding to their risk-taking levels, we use factor models following the common practice in the literature. The risk factors we consider include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The monthly data on these four risk factors from 2003 to

[4] Majority of the fund managers in our sample have a prior background as either an industry analyst or macro analyst, but not as both. Only 15 managers worked as both industry analysts and macro analysts. We classify these records by assigning managers with predominant experience in one type of job to the industry-only or macro-only subsample. This results in 3 records being classified, while the remaining 12 managers were removed due to ambiguous terms in office.

This article is protected by copyright. All rights reserved.

Accepted Article

2016 are sourced from China Asset Management Academy (CAMA).[5] The risk-free rate is the monthly interest rate on the one-year official deposit rate.[6]

Insert Table 1 about here

Table 1 reports the summary statistics of the entire sample as well as two subsamples: managers with background as industry analysts and managers with background as macro analysts. Over the sample period, the average monthly return of the total manager/month combination is 0.75% with a monthly standard deviation of 6.97%. The industry analyst group shows a monthly return of 0.81%, and the macro analyst group produces a monthly return of 0.53%. The Chinese stock market has an average 1.11% monthly excess return from 2003 to 2016. This high return, however, is associated with a large volatility with a monthly standard deviation of 9.20%. In the Chinese market, the size factor earns a large positive monthly return, 0.98%, and the momentum factor is associated with a negative monthly return, -0.22%. Out of all the Carhart four risk factors, the magnitude of the value factor is the lowest, only 0.08% per month.

2.2 Models

[5] CAMA also provides a detailed explanation on forming and calculation of these risk factors.

[6] This choice of risk-free rate is very common in Chinese studies, see, for example Lin, et al. (2013) and Pan, et al. (2015). The underlying reason is succinctly summarized by Pan, et al. (2015). In their footnote 13: "In China, Treasury-Bond maturity is usually three months or longer, and most Treasury Bonds have a maturity of one year or longer. A large proportion of Treasury Bonds are held by large banks, insurance companies, and other financial institutions. Limited accessibility to the general public and long maturity jointly disqualifies the Treasury interest rate as the risk-free rate. The interbank lending market, established in Shanghai in 2006, has a very short history and is not accessible to the general public. Bank deposits are implicitly insured by the government and can be considered as a default risk-free investment."

This article is protected by copyright. All rights reserved.

Accepted Article

Two widely used models in mutual fund studies that measure both stock-selection and market-timing abilities are the quadratic Treynor-Mazuy (TM) model (Treynor and Mazuy, 1966):

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \varepsilon_{p,t}, \quad (1)$$

and the asymmetric Henriksson-Merton (HM) model (Henriksson and Merton, 1981):

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \varepsilon_{p,t}, \quad (2)$$

where $r_{p,t+1}$ is the monthly return on portfolio p in excess of the risk-free rate during month t, MKT_t is the market excess return during month t, and $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. To properly account for different risk levels that fund managers take, we add additional risk factors, including size factor (SMB_t), value factor (HML_t), and momentum factor (MOM_t):

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \gamma_p g(MKT_t) + \varepsilon_{p,t}, \quad (3)$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model.

In model (3), α_p reflects managers' stock-picking skills and γ_p estimates market-timing performance. A positive estimated α_p favors the hypothesis that managers can successfully select underpriced stocks. A positive γ_p indicates market-timing ability. The logic is that when the market is up, the successful market-timing fund will be up by a disproportionate amount, and when the market is down, the fund will be down by a lesser amount, therefore, the fund's return bears a nonlinear relationship to the market factor.

In summary, we use the classical TM model and HM model to assess managers' stock-picking and market-timing skills separately. The market-timing skill is represented by the coefficient γ_p and the stock-picking skill is measured by the abnormal return α_p.

This article is protected by copyright. All rights reserved.

Accepted Article

3. Empirical Analysis

In this section, we examine whether mutual fund managers are capable of market timing and stock picking, as well as the differences in skills between two types of managers, by employing a series of empirical tests.

3.1 Portfolio results

We form equally-weighted portfolios of managers across the whole sample and two subsamples -- namely, the managers with industry analyst experience and those with macro analyst experience. We estimate the stock-picking ability, α_p, and the market-timing skill, γ_p, under both the TM and HM models while controlling for the Carhart risk factors. Table 2 presents the estimates for the whole sample and two subsamples respectively, as well as difference values between the two subsamples.

Insert Table 2 about here

In terms of stock-selection skill, the industry analyst portfolio scores higher, with a monthly alpha of 0.65% and 0.47% in the TM model and HM model, respectively. By contrast, the macro analyst portfolio only achieves a monthly alpha of 0.25% and 0.01%, as measured by the TM model and HM model, respectively. The differences in the monthly alpha of the two groups are statistically significant at the 10% level. In terms of market-timing skill, the macro analyst portfolio now seems dominant, with much higher coefficient γ_p estimates in both models. Measured by the TM model, the coefficient

This article is protected by copyright. All rights reserved.

Accepted Article

difference between the industry analyst portfolio and macro analyst portfolio is large in magnitude, -11.25%, which is significant at the 10% level. The difference between the two groups, however, is not statistically significant under the HM model despite its large magnitude. The results suggest that managers with a macro analyst background are better at timing the market than those with an industry analyst background.

3.2 Cross-sectional results

We also estimate parameters of model (3) for individual funds. We calculate *t*-statistics for the stock-picking skill measure α_p and market-timing coefficient γ_p across individual funds. We, therefore, have a distribution of *t*-statistics for each of the three groups: the full sample and two subsamples. Table 3 lists the percentage of *t*-statistics in each interval defined by a set of cutoff values. For instance, the column titled $t \geq 1.645$ reports the proportion of the funds with *t*-statistics falling in the interval $(1.645, \infty)$.

Insert Table 3 about here

Table 3 shows that the proportion of the *t*-statistics of α_p in the TM model greater than 2.326 is 5.81% for the managers with industry analyst backgrounds. Meanwhile, only 1.39% of the funds in the macro analyst group fall in this interval. Comparing the *t*-statistic distribution of α_p for the two subgroups, the industry analyst group shows a fat tail in the right-hand part while the macro analyst group concentrates more on the left and center parts. Comparing the *t*-statistic distribution of γ_p, the macro analyst funds are heavily tilted to the right while the other group has a heavier left tail. Overall, the distribution of the individual

This article is protected by copyright. All rights reserved.

Accepted Article

t-statistics suggests that the group of former industry analysts is better at stock picking, while the group of former macro analysts is better at market timing.

3.3 Bootstrap Tests

The portfolio analysis in section 3.1 and the cross-sectional distribution of t-statistics described in section 3.2 both lead to the conclusion that the past professional backgrounds of mutual fund managers explain their investment skills. Before drawing a final conclusion, however, we bear in mind that some funds might appear to be skillful simply by luck. Further, the validity of the aforementioned analyses hinges on the normality assumption, which is rarely the case for messy financial data. Therefore, we employ a bootstrap analysis by Cao et al. (2013) to examine whether the skills estimated above are simply pure luck.

Here we describe our bootstrap procedure using the TM stock-picking ability as an illustration. First, we estimate the TM model (3) for each fund, p, and store the parameter estimates for $\{\hat{\alpha}_p, \hat{\beta}_{p,1}, \hat{\beta}_{p,2}, \hat{\beta}_{p,3}, \hat{\beta}_{p,4}, \hat{\gamma}_p\}$, as well as the time series of residuals, $\{\varepsilon_{p,t}\}$. Second, we construct a time series of pseudo monthly fund returns based on the null hypothesis of no picking ability (i.e., $\alpha_p = 0$), $\{r^b_{p,t+1}\}$, as follows:

$$r^b_{p,t} = \hat{\beta}_{p,1} MKT_t + \hat{\beta}_{p,2}\, SML_t + \hat{\beta}_{p,3} HML_t + \hat{\beta}_{p,4} MOM_t + \hat{\gamma}_p MKT_t^2 + \varepsilon^b_{p,t}, \quad (4)$$

where $\{\varepsilon^b_{p,t}\}$ is the time series of bootstrapped residuals that are obtained through resampling $\{\varepsilon_{p,t}\}$ with replacement. In Equation (4), b is an index for the bootstrap iteration (b=1, 2, ..., M). Third, we estimate the TM model (3) on the pseudo fund returns $\{r^b_{p,t}\}$ and store the estimated stock-picking coefficient $\{\hat{\alpha}^b_p\}$ and its t-statistics $\{t^b_{\hat{\alpha}_p}\}$. By construction, the

This article is protected by copyright. All rights reserved.

Accepted Article

bootstrapped estimate should be zero. Any non-zero bootstrapped stock-picking estimate and its *t*-statistic are purely due to sampling variation. We then repeat the above process for all sample funds so that a specific cross-sectional statistic, the q-th percentile *t*-statistics across all of the sample funds, $t^b_{\hat{\alpha},q}$, can be obtained.

We repeat all the above steps for M iterations to generate a series of $t^b_{\hat{\alpha},q}$, $b = 1,2,\dots,M$. We then can use this series to approximate the empirical distribution of the q-th percentile cross-sectional *t*-statistics of the stock-selection coefficient under the null hypothesis of no picking ability. Finally, we use this empirical distribution to access the significance of the q-th percentile of the *t*-statistics of stock-selection coefficients estimated on the actual data, t_q. This is achieved by computing an empirical p-value as follows:

$$\text{p\_value} = \frac{1}{M}\sum_{b=1}^{M} I_{\left|t^b_{\hat{\alpha},q}\right|>\left|t_q\right|}, \quad (5)$$

where $I_{(.)}$ is an indicator function counting the frequency that the values of the bootstrapped cross-sectional statistic, $t^b_{\hat{\alpha},q}$, from M simulations exceed the actual value of the cross-sectional statistic t_q. The number of bootstrap simulations M is 1,000 in our analysis.

The empirical p-value we calculate using the above simulation procedure is robust, as it does not require any rigorous model assumptions. A small empirical p-value indicates strong evidence that the test result is unlikely to be attributed to random chance. Mutual fund managers, therefore, may possess genuine skill. A large p-value suggests weak evidence against the null hypothesis. We carry out the bootstrap analysis to test stock-picking and market-timing abilities under both the TM and HM models. In the

This article is protected by copyright. All rights reserved.

Accepted Article

examination of market-timing ability, we set $\gamma_i = 0$ in the bootstrap procedure. Table 4 and Table 5 report the top and bottom percentile (q = 1%, 5%, and 10%) of the cross-sectional *t*-statistics and the corresponding empirical p-values for the entire sample, as well as two subsamples from the bootstrap analysis.

Insert Table 4 and Table 5 here

Table 4 is for assessing stock-picking skill. The bootstrap analysis is conducted for the whole sample funds and two subsamples. The top panel is for the TM model and the bottom panel for the HM model. For any group, the *t*-statistics column reports the actual value of the cross-sectional *t*-statistic for a particular percentile. The p-value column is for the empirical p-value calculated from the simulations. The evidence supports that two subgroups possess different stock-picking skills. Under the TM model, for the industry analyst group, the t_qs for the top 1%, 5%, and 10% stock-picking funds are 3.21, 2.40, and 1.88, respectively, with the empirical p-values all close to zero. This supports a finding that the fund managers with industry analyst backgrounds enjoy stock-picking skills which cannot be simply attributed to good luck. In sharp contrast the t_qs for the top 1%, 5%, and 10% stock-picking funds in the macro analyst group are much lower, and none of the empirical p-values is smaller than 0.1. The results hold for the HM model as well. Table 4 suggests that the fund managers with industry analyst backgrounds are superior in terms of stock-picking skill compared with the fund managers with macro analyst backgrounds.

Table 5 is for assessing market-timing skill. When it comes to correctly timing the markets, the two groups again show noticeable differences. Under the TM model, the t_qs for the top 1% and 5% market-timing funds in the macro analyst group are 3.35 and 5.81,

This article is protected by copyright. All rights reserved.

Accepted Article

respectively, with the empirical p-values statistically significant at the 5% level. On the other hand the corresponding t_qs for the industry analyst group are smaller, and none is statistically significant. When we turn to the bottom quantiles, the evidence shows that the negative timing coefficients of the funds are largely due to random chance, and no strong conclusion can be drawn from our data. The pattern does not change when we switch from the TM model to the HM model. We take this evidence as the support for the claim that the fund managers with macro analyst backgrounds are generally better at timing the market compared to the fund managers with industry analyst backgrounds.

Insert Figure 1and Figure 2 about here

We also provide an alternative and more intuitive way to view the simulation results by presenting kernel density plots. Figure 1 displays the kernel density distributions of bootstrapped 5^{th} percentile *t*-statistics of alpha for the full sample, the industry analyst group, and the macro analyst group. The dashed vertical lines are the actual *t*-statistics of the stock-picking measures. Figure 2 plots the kernel density distributions of bootstrapped 5^{th} percentile *t*-statistics of the market-timing coefficients. Again, the dashed vertical lines are the actual *t*-statistics of the market-timing measures estimated from the real data. A vertical line toward extreme tails of a density plot is a sign of a significant deviation from the null hypothesis. As we can see, the industry group has extraordinary skill in picking undervalued stocks as indicated by the dash lines in the extreme right tails (Figure 1). The macro group possesses non-trivial market-timing abilities, shown by the dashed lines in the far right tails. Another important feature of the graphs is non-normality of the estimated skill coefficients. Hence, the bootstrap analysis is more suitable for this application than conventional analysis based on the normality assumption.

This article is protected by copyright. All rights reserved.

Accepted Article

In sum, the results outlined in this section indicate that top-ranked Chinese mutual fund managers can time the market and pick out stocks worthy of investment. More specifically, stock-picking ability exists only in those with backgrounds as industry analysts, and market-timing ability only in those with macro analyst backgrounds.

4. Alternative Explanations

The analysis in Section 3 supports a finding that the past professional backgrounds of mutual fund managers impact their investment skills. Specifically, mutual fund managers with past backgrounds as industry analysts excel in picking stocks, and mutual fund managers with past backgrounds as macro analysts are good at timing the markets. We attribute this skill difference between the two groups to the formation of human capital during their past work experiences. In this section, we carry out additional analysis to investigate our results against possible alternative explanations.

4.1 Other fund/manager characteristics

A source of concern is whether a fund manager's past work experience is correlated with some other fund and manager characteristics, which are the true underlying drivers of the performance. To rule out this concern, we regress the *t*-statistics of market-timing coefficient and alpha on a number of fund and manager characteristics:

$$\hat{t}_p = a + b_1 IndustryAnalyst_p + b_2 AGE_p + b_3 SIZE_p + b_4 TR_p + b_5 EXP_p + b_6 GEN_p + \epsilon_p, \qquad (6)$$

This article is protected by copyright. All rights reserved.

Accepted Article

where $\hat{t}_p$ is the *t*-value of either $\hat{\alpha}_p$ or $\hat{\gamma}_p$ of manager p using Model (3); $Industry\ Analyst_p$ is a dummy variable that takes 1 if the manager worked as an industry analyst, and 0 otherwise; AGE_p, $SIZE_p$, TR_p, and EXP_p are the averages of the funds' total net assets (in logarithm), turnover ratios, and expense ratios that manager p ever managed, respectively; GEN_p is the gender of manager p.

Insert Table 6 about here

Table 6 reports the regression results of Model (6). As we can see, even after controlling for observable fund and manager characteristics, managers' prior work experience has a significant impact on their investment skills. A background as an industry analyst promotes stock-picking skills, with positive coefficients on *t*-value of alpha, 0.508 and 0.416 in the TM and HM models respectively. Such experience has a negative influence on *t*-value of the market-timing coefficients, which indicates that having worked as a macro analyst is beneficial in promoting market-timing skill. We also find significant and negative relationship between *t*-values of alpha and each of the two fund characteristics: fund expense ratio and fund turnover. Further, the relationship between fund age and market-timing ability seems to be significantly positive.

4.2 Time-varying investment opportunities

Another source of concern is whether stock-picking and market-timing measures are estimated for all managers over similar periods. Suppose, for instance, that the opportunities

This article is protected by copyright. All rights reserved.

Accepted Article

to successfully pick stocks and time the market change through over time for managers as a whole. Suppose also that macro analysts and industry analysts tend to enter and exit the sample at different points in time. Under this scenario, each group would display different abilities on average, but for reasons unrelated to the formation of human capital. To rule out this possibility, we investigate whether the presence of two types of managers over time are correlated with the market conditions differently. For each type of manager, we calculate the proportion of operational managers[7] in a month to the overall number of managers in that category. The proportion at month t is denoted as π_t^i, with $i = 1$ for the industry analyst group and $i = 2$ for the macro analyst group. We then compute the following correlation,

$$\tau_i = \text{cor}\left(\pi_t^i, g(MKT_t)\right), \qquad i = 1, 2, \quad (7)$$

where $g(MKT_t)$ is a monthly market condition proxy, taking values as either MKT_t^2 or $Max(MKT_t, 0)$. If τ_1 is indifferent from τ_2, we would be confident that our analysis is not biased by different types of managers "timing" the market to enter or exit. Since τ_1 and τ_2 are not independent, and there is no standard procedure available to test two correlated correlation coefficients, we again rely on bootstrap. Our bootstrap procedure has four steps.

1. Resample 168 monthly records $(\pi_t^1, \pi_t^2, g(MKT_t))$ with replacement and obtain a new time series of triples of length 168. Calculate correlation (7) and denote as $\tau_i^b, i = 1, 2;\ b = 1, 2, \cdots, M$, where the superscript b refers to the b-th bootstrap sample, and M is the bootstrap iteration.

2. Apply the Fisher transformation on $\tau_i^b, i = 1, 2$,

$$z_i^b = \frac{1}{2}\ln\left(\frac{1+\tau_i^b}{1-\tau_i^b}\right),$$

[7] A manager who reports a fund return in a month in our sample is termed as an operational manager for that month.

This article is protected by copyright. All rights reserved.

Accepted Article

and then calculate $d^b = z_1^b - z_2^b$. The Fisher transformation serves the purpose of transforming the sampling distribution of the correlation coefficient τ_i so that it becomes approximately normally distributed. As a result, the difference of two transformed correlations is also normally distributed. Under the null hypothesis that τ_1 is indifferent from τ_2, d^b is a normal distribution with mean zero.

3. Calculate the standard error of the difference of two transformed correlations based on M bootstrap samples $d^b, b = 1, 2, \cdots, M$, and denote it as σ_d^2.

4. Under the null distribution of a normal distribution with mean zero and variance σ_d^2, calculate p-value of the observed difference of the transformed correlations on the actual data, $d = z_1 - z_2$, where $z_i = \frac{1}{2}\ln(\frac{1+\tau_i}{1-\tau_i})$, $i = 1, 2$.

Table 7 reports the correlation coefficients of the participation rates of two types of managers with the market conditions and the statistical test of the difference between these two correlation coefficients. Neither type of manager seems to "time" the market as to when to get involved, as shown by the low correlations of their participation rates with the market conditions. When MKT_t^2 is used as a measure of market-timing opportunity, the correlations are -0.05 for the industry analyst group and -0.10 for the macro analyst group. When $Max(MKT_t, 0)$ is used as a measure of market-timing opportunity, the correlations for the industry analyst group and the macro analyst group are 0.01 and -0.02, respectively. Overall, the macro analyst group displays a slightly higher negative correlation with the market conditions. However, based on our bootstrap-based tests, it is not statistically different from the industry analyst group as evidenced by the large p-values no matter which market condition proxy in use. We can, therefore, rule out the possibility that our analysis is biased by two types of managers participating in the market under different conditions.

This article is protected by copyright. All rights reserved.

Accepted Article

4.3 Incentive bias

Last, we examine whether managers have an incentive bias toward one skill over the other. This incentive bias is related to fund managers' attention allocation. For example, if market timing is costly to the manager because the reward is low, it would be optimal for the manager to spend fewer resources in market timing when volatility is low; that does not imply that the manager is less skillful. To address this concern, we compare actual rewards of the market-timing skill versus stock-picking skill. If both skills can translate into comparable performances, the managers in our sample should have no strong incentive to promote one skill and suppress the other. For this purpose, we follow Bollen and Busse (2005) to calculate actual market-timing success as

$$\mu_p = \frac{1}{N_p} \sum_{t=1}^{N_p} g(MKT_t),$$

where N_p is the number of operating months of the manager p in our sample, the convex term $g(MKT_t)$ takes the form as either MKT_t^2 or $Max(MKT_t, 0)$. Hence, μ_p is the average value of the market-timing success over the period in which the manager is active. The stock-picking success of the manager p is simply measured by the manager's alpha obtained by either the TM model or the HM model.

Table 8 lists the market-timing and the stock-picking successes of all the managers in our sample. As we can see, under the TM model framework, two types of skills can be translated into similar performance on average: 0.06% per month for stock picking and 0.04% per month for market timing. The value added based on stock picking spans a wider range, though, with a standard deviation of 0.70 compared with 0.37 for the market-timing skill. Under the HM model framework, the value added associated with both skills is similar in variation, but market timing seems to be associated with higher reward on average, with 0.10% per month extra return compared with 0.03% based on stock picking. Overall,

This article is protected by copyright. All rights reserved.

Accepted Article

the evidence shows that both stock picking and market timing are rewarding in Chinese markets. This result gives managers a level playing field to utilize their full skills, whether they are stock pickers or market timers.

5. Robustness

This section conducts additional checks in order to examine the robustness of our results in different model settings. First, we repeat the whole analysis adjusting for the classic Fama-Fench three risk factors rather than the Carhart four factors. This analysis yields similar and even stronger results. For brevity, we do not tabulate the three-factor results here which are available upon request. We also extend our bootstrap analyses considering time-series correlation and bond investment and report the results below.

5.1 Controlling for time-series correlation

The bootstrap analysis in Section 3.3 assumes that the regression residuals are independent. However, the residuals may well serially correlate over time. To control for this time-series correlation, we conduct a bootstrap analysis by including the lagging market conditions during the previous month:

$$r_{p,t} = \alpha_p + \beta_{p,1} MKT_t + \beta_{p,2} SMB_t + \beta_{p,3} HML_t + \beta_{p,4} MOM_t + \beta_{p,5} MKT_{t-1} + \beta_{p,6} SMB_{t-1} + \beta_{p,7} HML_{t-1} + \beta_{p,8} MOM_{t-1} + \gamma_p g(MKT_t) + \varepsilon_{p,t}, \quad (8)$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model.

Insert Table 9 and Table 10 about here

This article is protected by copyright. All rights reserved.

Accepted Article

Table 9 and Table 10 show the bootstrap analysis for cross-sectional *t*-statistics of estimated alpha and timing coefficient controlling for the lagging market factors. Consistent with the evidence in Table 4 and Table 5, the industry analyst group excels at picking stocks and the macro analyst group is better at timing markets. Even when time-series influence is taken into consideration, the skills of the two groups and the differences between them remain significant.

5.2 Controlling bond return

A substantial portion of the funds in our sample bear considerable exposure to bond markets. On average, the proportion of bonds investment in the total net assets of the funds in our sample is 8.33%, as disclosed in their 2015 annual report. We also notice that the fixed income exposure in our sample focuses on Treasury bonds. We, therefore, add the monthly Treasury bond yield into model (3):

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \gamma_p g(MKT_t) + \varepsilon_{p,t}, \quad (9)$$

where $BOND_t$ is the Treasury bond yield, and the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model.

Insert Table 11 and Table 12 about here

Table 11 and Table 12 report the bootstrap analysis for cross-sectional *t*-statistics of estimated alpha and timing coefficient while controlling for bond returns. The result indicates

This article is protected by copyright. All rights reserved.

Accepted Article

that investment skills and the difference between the two groups remain robust after controlling for bond market conditions. In Table 11, the top 1%, 5% and 10% of the stock-picking funds in the industry analyst group cannot be simply attributed to luck, but luck seems to explain most performances of the top stock pickers in the macro analyst group. Interestingly, after controlling for bond returns, the negative alphas of some funds in the industry analyst group can no longer be due simply to random chance. For example, the empirical p-values associated with bottom-ranked stock pickers in the industry analyst group are close to zero. The results in Table 12 confirm the robustness of the market-timing skill of the macro analyst group, with empirical *p*-values of the top 1st and 5th percentiles are significant regardless of the model used.

6. Conclusion

This paper examines the relationship between Chinese mutual fund managers' prior work experience and their investment skills. We focus on the set of managers with prior work experience either as industry analysts or as macro analysts. The research question that interests us is whether the comparative advantage managers accumulated along their career paths can significantly influence and differentiate their investment skills.

Using a sample of 330 equity-oriented active Chinese mutual fund managers' performance data from the period between 2003 and 2016, we report strong evidence that market-timing skills and stock-picking skills exist among Chinese mutual fund managers. More detailed analysis shows that there is a significant effect by managers' past professional backgrounds on their investment skills. Specifically, managers of industry analyst backgrounds exhibit significant stock-picking skills, while those of macro analyst backgrounds do not. The latter group, however, is better at market timing, a skill in which the other type of managers does not excel. The pattern is the same under both the TM and HM

This article is protected by copyright. All rights reserved.

Accepted Article

models. We apply the bootstrap analysis to provide robust statistical inferences. The bootstrap analysis suggests that the skills of top-ranked managers cannot be attributed merely to luck; rather, they are products of genuine skills. Our results are not biased by any potential sample bias associated with the unbalanced nature of the panel, and the hypotheses are also supported by the data even after controlling for observable fund and manager characteristics.

Although this research is carried out using Chinese data, we believe that a mutual fund manager's past professional background has a broader impact on performance. These results are informative for investors and fund companies. They indicate that investors, in their relentless search for funds with superior performance, should consider the prior work experience of fund managers. Similarly, funds that wish to optimize performance also need to consider this prior work experience when employing managers.

References

Bollen, Nicolas P.B. and Busse, Jeffery A. 2005. Short-Term Persistence in Mutual Fund Performance, *Review of Financial Studies* 18, 569-597.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W. Lo, 2013. Can hedge funds time market liquidity?„*Journal of Financial Economics* 109, 493-516.

This article is protected by copyright. All rights reserved.

Accepted Article

Chen, Keqi, Chen, Rui, Zhang, Xueyong and Zhu, Min, 2016. Chinese Stock Market Return Predictability: Adaptive Complete Subset Regressions, *Asia-Pacific Journal of Financial Studies* 45, 779-804.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008. The Small World of Investing: Board Connections and Mutual Fund Returns, *Journal of Political Economy* 116, 951-979.

Dass, Nishant, Vikram Nanda, and Qinghai Wang, 2013. Allocation of Decision Rights and the Investment Strategy of Mutual Funds, *Journal of Financial Economics* 110, 254-277.

Fama, Eugene F., and Kenneth R. French, 1993.Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Golec, Joseph H. 1996. The Effects of Mutual Fund Managers Characteristic on Their Portfolio Performance, Risk and Fees.*Financial Services Review*5(2): 133 –148.

Gottesman, Aron A., and Matthew R. Morey, 2006.Manager education and mutual fund performance, *Journal of Empirical Finance* 13, 145-182.

Henriksson, Roy D., and Robert C. Merton, 1981. On Market Timing and Investment Performance, *Journal of Business* 54, 513-533.

Huang, Songnan, Jing Shi, Lu Zheng and Qiaoqiao Zhu 2015. Work Experience and Managerial Performance: Evidence from Mutual fund Managers. Working paper.

Merton, Robert C., 1981. On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts, *Journal of Business* 54, 363-406.

Patel, Saurin and Sarkinssian, Sgergei, 2017. To Group or Not to Group? Evidence from Mutual Fund Databases, *Journal of Financial and Quantitative Analysis, forthcoming*.

Sonney, Frédéric, 2009. Financial Analysts' Performance: Sector Versus Country Specialization, *Review of Financial Studies* 22, 2087-2131.

Treynor, Jack L., and Kay K. Mazuy, 1966. Can Mutual Funds Outguess the Market?,*Harvard Business Review* 44, 131-136.

This article is protected by copyright. All rights reserved.

Accepted Article

Wang, Diamond, 2016. What Does it Mean to be in a Team? Evidence from U.S. Mutual Fund Managers, *working paper,* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2825534.

This article is protected by copyright. All rights reserved.

Accepted Article

Table 1

Summary statistics

This table presents summary statistics of the data. The sample period is from 2003 to 2016. The first three rows are monthly returns of mutual funds for the whole sample, the managers with industry analyst background and the managers with macro analyst background. N is the number of manager-month combination. The Carhart risk factor returns for Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM) are also summarized in the table. The risk-free rate is the monthly interest rate on one-year official deposit rate.

	N	Mean	STD	Quantile				
				1%	**25%**	**50%**	**75%**	**99%**
Return (All) (%)	16216	0.75	6.97	-18.93	-2.03	0.50	3.27	19.86
Return (Industry analyst) (%)	12852	0.81	7.26	-19.34	-2.12	0.59	3.47	19.93
Return (Macro analyst) (%)	3364	0.53	5.76	-18.03	-1.74	0.26	2.55	18.40
MKT (%)	168	1.11	9.20	-26.97	-4.34	1.49	5.77	20.24
SMB (%)	168	0.98	4.69	-11.52	-1.66	0.93	3.64	11.47
HML (%)	168	0.08	3.19	-7.31	-1.90	-0.02	1.86	8.03
MOM(%)	168	-0.22	4.12	-11.88	-2.94	-0.17	2.54	11.64

Table 2

Portfolio results

This table reports the estimation results for

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market

This article is protected by copyright. All rights reserved.

excess return in month t. $r_{p,t}$ is the excess return on equally-weighted manager returns in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The estimate α measures stock-picking skill. The coefficient *γ* measures market-timing skill. Panel A and Panel B reports the results of estimate α_p (in percent) for the whole sample, the industry analyst group, and the macro analyst group. The difference values between the two subsample groups are also reported. Panel C and Panel D shows corresponding results of coefficient *γ* (in percent). T-statistics are calculated based on Newey and West heteroscedasticity and autocorrelation-consistent standard errors with two lags. ***, ** and * indicate significance at the1%, 5% and 10% levels, respectively.

	Estimate	***T*-statistic**	***P*-value**
Panel A : Statistics of Carhart alpha(TM model)			
All Funds	0.59***	3.45	0.00
Industry Analyst	0.65***	3.90	0.00
Macro Analyst	0.25*	1.90	0.06
Difference value (Industry Analyst-Macro Analyst)	0.40*	1.88	0.06
Panel B : Statistics of Carhart alpha (HM model)			
All Funds	0.40*	1.76	0.08
Industry Analyst	0.47**	2.20	0.03
Macro Analyst	0.01	0.08	0.94
Difference value (Industry Analyst-Macro Analyst)	0.46*	1.86	0.06
Panel C : Statistics of market-timing coefficients (TM model)			
All Funds	9.90*	1.71	0.09
Industry Analyst	6.73	1.60	0.11
Macro Analyst	17.98***	3.41	0.00
Difference value (Industry Analyst-Macro Analyst)	-11.25*	-1.66	0.10

This article is protected by copyright. All rights reserved.

Accepted Article

Panel D : Statistics of market-timing coefficients (HM model)			
All Funds	8.58	1.21	0.23
Industry Analyst	7.65	1.32	0.19
Macro Analyst	12.18**	2.01	0.04
Difference value (Industry Analyst-Macro Analyst)	-4.53	-0.97	0.32

	Percentage of the Funds

Table 3

Cross-sectional distribution of *t*-statistics

This table presents the distribution of *t*-statistics for stock-picking coefficient and market-timing coefficient. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The estimate α measures stock-picking skill. The coefficient γ measures market-timing skill. The numbers in the table reflect the percentages of t-statistics satisfied the conditions. Panel A and Panel B reports the results of estimate α for the whole sample, sample of industry analyst group, sample of macro analyst group. Panel C and Panel D shows corresponding results of coefficient γ . T-statistics are calculated based on Newey and West heteroscedasticity and autocorrelation-consistent standard errors with two lags.

This article is protected by copyright. All rights reserved.

Accepted Article

Accepted Article

	Number of Funds	t≤-2.326	t≤-1.960	t≤-1.645	t≥1.645	t≥1.960	t≥2.326
Panel A : Statistics of Carhart alpha(TM model)							
All Funds	330	3.94	6.36	9.09	11.52	7.27	4.85
Industry Analyst	258	3.10	5.43	7.75	12.79	8.53	5.81
Macro Analyst	72	6.94	9.72	13.89	6.94	2.78	1.39
Panel B : Statistics of Carhart alpha(HM model)							
All Funds	330	3.03	4.55	9.09	7.88	3.94	1.52
Industry Analyst	258	2.71	3.88	8.14	8.53	4.65	1.94
Macro Analyst	72	4.17	6.94	12.50	5.56	1.39	0.00
Panel C : Statistics of market-timing coefficients (TM model)							
All Funds	330	2.42	5.15	10.00	13.64	9.09	6.36
Industry Analyst	258	3.10	5.43	10.85	14.34	9.69	6.20
Macro Analyst	72	0.00	4.17	6.94	11.11	6.94	6.94
Panel D : Statistics of market-timing coefficients (HM model)							
All Funds	330	1.21	1.82	5.76	14.55	9.70	6.06
Industry Analyst	258	1.16	1.94	6.59	15.50	10.08	5.81
Macro Analyst	72	1.39	1.39	2.78	11.11	8.33	6.94

Table 4

Bootstrap analysis of stock picking

This article is protected by copyright. All rights reserved.

Accepted Article

This table presents the results of bootstrap analysis for alpha. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The estimate α measures stock-picking skill. In the table, Panel A and Panel B are for the TM model and the HM model, respectively. The first row reports the sorted Newey-West *t*-statistics of estimate alpha across individual funds, reflecting stock-picking skill, and the second row is the empirical *p*-values from bootstrap simulations. The number of resampling iterations is 1,000.

	bottom	top

This article is protected by copyright. All rights reserved.

Accepted Article

		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of Carhart alpha (TM model)							
All Funds	*t*-stat	-2.94	-2.18	-1.60	1.76	2.30	3.17
	p-value	0.87	0.90	0.96	0.00	0.00	0.00
Industry Analyst	*t*-stat	-2.65	-2.13	-1.52	1.88	2.40	3.21
	p-value	0.51	0.93	0.79	0.00	0.00	0.01
Macro Analyst	*t*-stat	-3.70	-2.80	-1.80	1.34	1.90	2.33
	p-value	0.89	0.95	0.96	0.14	0.10	0.54
Panel B: Cross-section statistics of Carhart alpha (HM model)							
All Funds	*t*-stat	-2.87	-1.94	-1.60	1.46	1.83	2.38
	p-value	0.68	0.42	0.65	0.00	0.01	0.19
Industry Analyst	*t*-stat	-2.87	-1.88	-1.45	1.53	1.94	2.52
	p-value	0.62	0.25	0.14	0.00	0.00	0.21
Macro Analyst	*t*-stat	-3.16	-2.05	-1.69	1.15	1.70	1.97
	p-value	0.67	0.62	0.78	0.43	0.28	0.83

Table 5

Bootstrap analysis of market timing

This table presents the results of the bootstrap analysis for the market-timing coefficient. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

This article is protected by copyright. All rights reserved.

Accepted Article

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The coefficient γ measures market-timing skill. In the table, Panel A and Panel B respectively show results of TM model and HM model. The first row reports the sorted Newey-West *t*-statistics of timing coefficients across individual funds, reflecting market-timing skill, and the second row is the empirical *p*-values from bootstrap simulations. The number of resampling iterations is 1,000.

		bottom			top		
		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of market-timing coefficients (TM model)							
All Funds	*t*-stat	-2.63	-2.02	-1.65	1.86	2.50	4.07
	p-value	0.86	0.23	0.02	0.84	0.66	0.26
Industry Analyst	*t*-stat	-2.64	-2.15	-1.76	1.96	2.50	3.72
	p-value	0.87	0.15	0.01	0.63	0.68	0.60
Macro Analyst	*t*-stat	-2.24	-1.75	-1.52	1.66	3.35	5.81
	p-value	0.88	0.63	0.24	0.84	0.04	0.04
Panel B: Cross-section statistics of market-timing coefficients (HM model)							
All Funds	*t*-stat	-2.37	-1.75	-1.23	1.93	2.56	3.70
	p-value	0.78	0.33	0.48	0.18	0.06	0.11
Industry Analyst	*t*-stat	-2.65	-1.81	-1.38	1.98	2.54	3.40
	p-value	0.46	0.26	0.13	0.17	0.12	0.40
Macro Analyst	*t*-stat	-2.37	-1.31	-1.07	1.69	3.48	4.48

This article is protected by copyright. All rights reserved.

p-value	0.69	0.91	0.73	0.61	0.00	0.07

Table 6

Controlling for fund/manager characteristics

This table presents the results for cross-sectional regression of t-statistics of market timing coefficient and alpha respectively from TM model and HM model on fund characteristics:

	Market-timing	Alpha

$$\hat{t}_p = a + b_1 IndustryAnalyst_p + b_2 AGE_p + b_3 SIZE_p + b_4 TR_p + b_5 EXP_p + b_6 GEN_p + \epsilon_p,$$

where $\hat{t}_p$ is the t-value of market-timing coefficients or alpha on manager *p* estimated using the four-factor model (3). $Industry\ Analyst_p$ is a dummy variable that takes 1 if the manager worked as an industry analyst, and 0 otherwise; AGE_p, $SIZE_p$, TR_p, and EXP_p are the averages of the funds' total net assets (in logarithm), turnover ratios and expense ratios that manager *p* ever managed, respectively; GEN_p is the gender of manager *p*. The results are reported for market timing coefficient and alpha, respectively. ***, ** and * indicate significance at the1%, 5% and 10% levels, respectively.

This article is protected by copyright. All rights reserved.

Accepted Article

Accepted Article

Model	TM	HM	TM	HM
Industry Analyst	-0.10	-0.10	0.51***	0.42***
	(-0.56)	(-0.61)	(3.08)	(2.77)
GEN	-0.00	-0.09	0.37*	0.36*
	(-0.01)	(-0.401)	(1.72)	(1.83)
AGE	0.56**	0.61***	0.54**	0.15
	(2.29)	(2.74)	(2.48)	(0.77)
EXP	-4.20	6.02	-103.33**	-92.02**
	(-0.08)	(0.12)	(-2.13)	(-2.08)
TR	8.96	6.84	-14.03**	-13.12***
	(1.44)	(1.21)	(-2.53)	(-2.60)
SIZE	-0.05**	-0.08	-0.12	-0.06
	(-0.33)	(-0.68)	(-1.05)	(-0.54)
Constant	-2.22*	-2.33**	-0.12	1.03
	(-1.76)	(-2.04)	(-0.11)	(1.00)
Observations	297	297	297	297
Adjusted R-squared	0.184	0.180	0.256	0.200

This article is protected by copyright. All rights reserved.

Accepted Article

Table 7

Correlation of participation rates with the market condition.

This table shows the correlation coefficients of the participation rates of two types of managers with the market condition and the statistical test of the difference between these two correlation coefficients. Participation rates are the proportion of operational managers in a month to the overall number of managers in that category. The proportion at month t is denoted as π_t^i, with $i = 1$ for the industry analyst group and $i = 2$ for the macro analyst group. We then compute the following correlation,

$$\tau_i = \text{cor}\left(\pi_t^i, g(MKT_t)\right), \qquad i = 1, 2,$$

where $g(MKT_t)$ is a monthly market condition proxy, taking values as either MKT_t^2 or $Max(MKT_t, 0)$. Transform Diff is denoted as $d = z_1 - z_2$, where $z_i = \frac{1}{2}\ln(\frac{1+\tau_i}{1-\tau_i})$. We use bootstrap method (M=1000) to calculate the standard error of the difference of two transformed correlations and calculate the *p*-value.

$g(MKT_t)$	Industry Analyst	Macro Analyst	Transform Diff	*P*-value
MKT_t^2	-0.05	-0.10	0.05	0.88
$Max(MKT_t, 0)$	0.01	-0.02	0.03	0.93

Table 8

Stock-picking and market-timing successes.

This table lists the market-timing and the stock-picking successes of all the managers in our sample. α_p measures the stock-picking success of the manager p obtained by either the TM model or the HM model. μ_p is the average value of the market-timing success over the period in which the manager is active.

This article is protected by copyright. All rights reserved.

Accepted Article

$\mu_p = \frac{1}{N_p}\sum_{t=1}^{N_p} g(MKT_t)$, where N_p is the number of operating months of the manager p in our sample, the convex term $g(MKT_t)$ takes the form as either MKT_t^2 or $Max(MKT_t, 0)$.

		N	Mean	STD	Quantile				
					1%	25%	50%	75%	99%
TM Model	$\alpha_p(\%)$	330	0.06	0.70	-1.96	-0.31	-0.03	0.37	1.93
	$\mu_p(\%)$	330	0.04	0.37	-0.93	-0.14	0.02	0.21	1.00
HM Model	$\alpha_p(\%)$	330	0.03	1.75	-2.27	-0.43	-0.06	0.35	2.02
			bottom				top		

Table 9

Bootstrap analysis of stock picking controlling for time-series correlation

This table presents the results of bootstrap analysis for alpha. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

This article is protected by copyright. All rights reserved.

Accepted Article

		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of Carhart alpha (TM model)							
All Funds	*t*-stat	-2.96	-1.94	-1.41	1.87	2.23	3.07
	p-value	0.85	0.81	0.59	0.00	0.00	0.04
Industry Analyst	*t*-stat	-2.51	-1.66	-1.37	1.93	2.37	3.17
	p-value	0.30	0.13	0.45	0.00	0.00	0.05
Macro Analyst	*t*-stat	-3.65	-2.72	-1.72	1.36	1.67	2.13
	p-value	0.88	0.99	0.94	0.33	0.56	0.83
Panel B: Cross-section statistics of Carhart alpha (HM model)							
All Funds	*t*-stat	-2.63	-1.86	-1.39	1.40	1.78	2.52
	p-value	0.35	0.35	0.16	0.05	0.15	0.38
Industry Analyst	*t*-stat	-2.41	-1.83	-1.28	1.57	1.86	2.78
	p-value	0.10	0.25	0.03	0.01	0.08	0.17
Macro Analyst	*t*-stat	-3.41	-2.16	-1.77	1.22	1.39	1.88
	p-value	0.82	0.83	0.92	0.53	0.88	0.93

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The estimate $\propto$ measures stock-picking skill. In the table, Panel A and Panel B respectively show results of TM model and HM model. The first row reports the sorted Newey-West *t*-statistics of estimate alpha across individual funds, reflecting stock-picking skill, and the second row is the empirical *p*-values from bootstrap simulations. The number of resampling iterations is 1,000.

This article is protected by copyright. All rights reserved.

Accepted Article

Table 10

Bootstrap analysis of market timing controlling for time-series correlation

This table presents the results of bootstrap analysis for the market-timing coefficient. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the

		bottom			top		
		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of market-timing coefficients (TM model)							
All Funds	*t*-stat	-2.51	-1.94	-1.44	1.85	2.58	4.45
	p-value	0.87	0.28	0.27	0.52	0.14	0.02
Industry Analyst	*t*-stat	-2.52	-1.99	-1.47	1.86	2.45	3.64
	p-value	0.86	0.26	0.21	0.56	0.44	0.39
Macro Analyst	*t*-stat	-2.32	-1.70	-1.39	1.70	4.04	6.31
	p-value	0.86	0.70	0.40	0.62	0.00	0.01
Panel B: Cross-section statistics of market-timing coefficients (HM model)							
All Funds	*t*-stat	-2.35	-1.67	-1.13	1.84	2.32	3.89
	p-value	0.75	0.51	0.87	0.17	0.18	0.02
Industry Analyst	*t*-stat	-2.48	-1.73	-1.23	1.97	2.32	3.40
	p-value	0.60	0.39	0.52	0.06	0.29	0.24
Macro Analyst	*t*-stat	-2.35	-1.35	-1.06	1.76	3.03	4.67
	p-value	0.73	0.91	0.79	0.30	0.01	0.04

Accepted Article

market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The coefficient γ measures market-timing ability. In the table, Panel A and Panel B respectively show results of TM model and HM model. The first row reports the sorted Newey-West t-statistics of timing coefficients across individual funds, reflecting market-timing skill, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 1,000.

Table 11

Bootstrap analysis of stock picking controlling bond return

This table presents the results of bootstrap analysis for alpha. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we estimate

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where $BOND_t$ is the Treasury bond yield, and the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The estimate $\propto$ measures stock-picking skill. In the table, Panel A and Panel B respectively show results of TM model and HM model. The first row reports the sorted Newey-West t-statistics of estimate alpha across individual funds, reflecting stock-picking skill, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 1,000.

This article is protected by copyright. All rights reserved.

Accepted Article

Table 12

Bootstrap analysis of market timing controlling bond return

This table presents the results of bootstrap analysis for the market-timing coefficient. For the samples of all funds, the industry analyst group and the macro analyst group (at least 24 monthly return observations), we

		bottom			top		
		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of Carhart alpha (TM model)							
All Funds	*t*-stat	-2.64	-1.53	-0.94	1.83	2.33	3.14
	p-value	0.20	0.00	0.00	0.00	0.00	0.01
Industry Analyst	*t*-stat	-2.62	-1.48	-0.88	1.94	2.51	3.46
	p-value	0.20	0.00	0.00	0.00	0.00	0.00
Macro Analyst	*t*-stat	-2.85	-2.06	-1.27	1.39	1.60	2.53
	p-value	0.39	0.48	0.06	0.10	0.45	0.43
Panel B: Cross-section statistics of Carhart alpha (HM model)							
All Funds	*t*-stat	-2.47	-1.50	-1.21	1.67	2.00	2.82
	p-value	0.03	0.00	0.00	0.00	0.00	0.05
Industry Analyst	*t*-stat	-2.62	-1.46	-1.13	1.76	2.16	2.88
	p-value	0.16	0.00	0.00	0.00	0.00	0.07
Macro Analyst	*t*-stat	-2.37	-2.00	-1.36	1.28	1.51	2.29
	p-value	0.11	0.37	0.09	0.17	0.52	0.56

This article is protected by copyright. All rights reserved.

Accepted Article

estimate

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \gamma_p g(MKT_t) + \varepsilon_{p,t},$$

where $BOND_t$ is the Treasury bond yield, and the function $g(MKT_t)$ takes the form MKT_t^2 in the TM model and $Max(MKT_t, 0)$ in the HM model. MKT_t^2 is square of monthly market excess return in month t. $Max(MKT_t, 0)$ is the positive part of the market excess return in month t. $r_{p,t}$ is the excess return on each individual fund in month *t*. The independent variables include Chinese market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The coefficient γ measures market-timing skill. In the table, Panel A and Panel B respectively show results of TM model and HM model. The first row reports the sorted Newey-West *t*-statistics of timing coefficients across individual funds, reflecting market-timing skill, and the second row is the empirical *p*-values from bootstrap simulations. The number of resampling iterations is 1,000.

		bottom			top		
		1%	5%	10%	10%	5%	1%
Panel A: Cross-section statistics of market-timing coefficients (TM model)							
All Funds	*t*-stat	-2.59	-2.12	-1.57	1.89	2.46	4.15
	p-value	0.89	0.10	0.06	0.81	0.71	0.17
Industry Analyst	*t*-stat	-2.85	-2.13	-1.69	1.90	2.38	3.42
	p-value	0.69	0.15	0.02	0.76	0.85	0.84
Macro Analyst	*t*-stat	-2.20	-1.54	-1.45	1.68	3.32	5.83
	p-value	0.90	0.85	0.29	0.83	0.04	0.03
Panel B: Cross-section statistics of market-timing coefficients (HM model)							
All Funds	*t*-stat	-2.30	-1.71	-1.22	1.97	2.54	3.67
	p-value	0.84	0.41	0.53	0.14	0.08	0.13
Industry Analyst	*t*-stat	-2.55	-1.78	-1.34	1.98	2.53	3.39
	p-value	0.59	0.30	0.24	0.18	0.15	0.43
Macro Analyst	*t*-stat	-2.30	-1.25	-1.08	1.70	3.46	4.45

This article is protected by copyright. All rights reserved.

Accepted Article

p-value	0.73	0.95	0.70	0.59	0.00	0.08

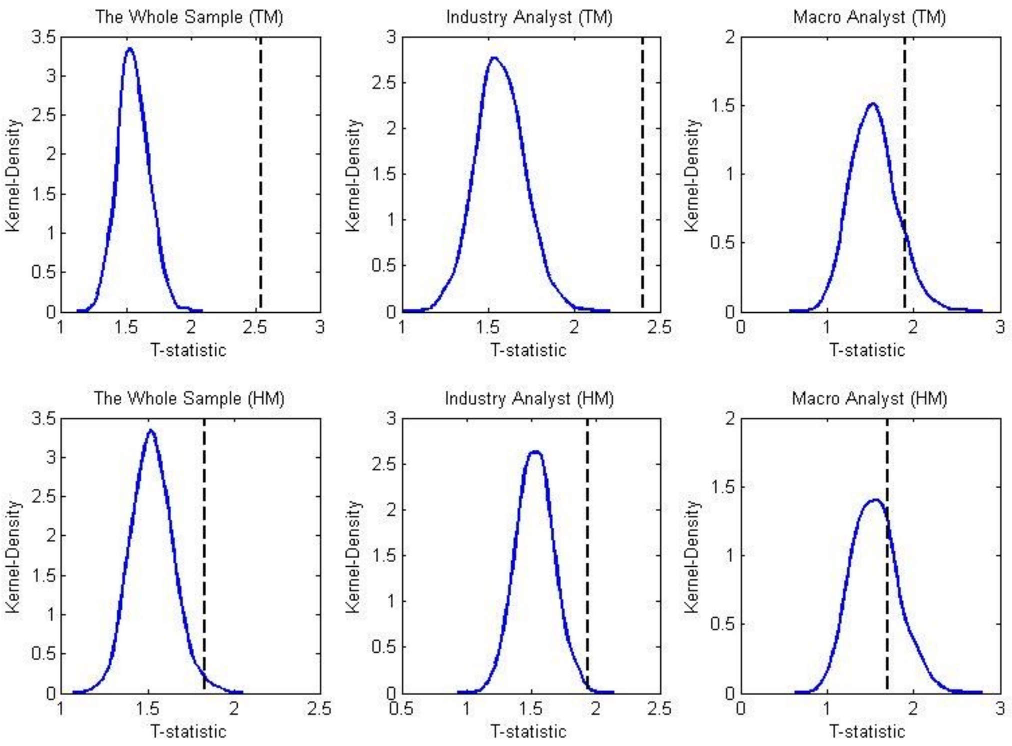

Fig.1. The 5th percentile cross-sectional t-statistics of alpha.

This figure plots the 5th percentile cross-sectional t-statistics of alpha using the TM model and the HM: actual fund vs. bootstrapped funds. The solid line is kernel density estimate based on 1000 bootstrap simulations, while the dashed line is for the actual t-statistics of alpha calculated on the real data. The graphics from left to right are for the whole sample, the industry analyst group and the macro analyst group. The top panel is for the TM model and the bottom panel is for the HM model.

This article is protected by copyright. All rights reserved.

Accepted Article

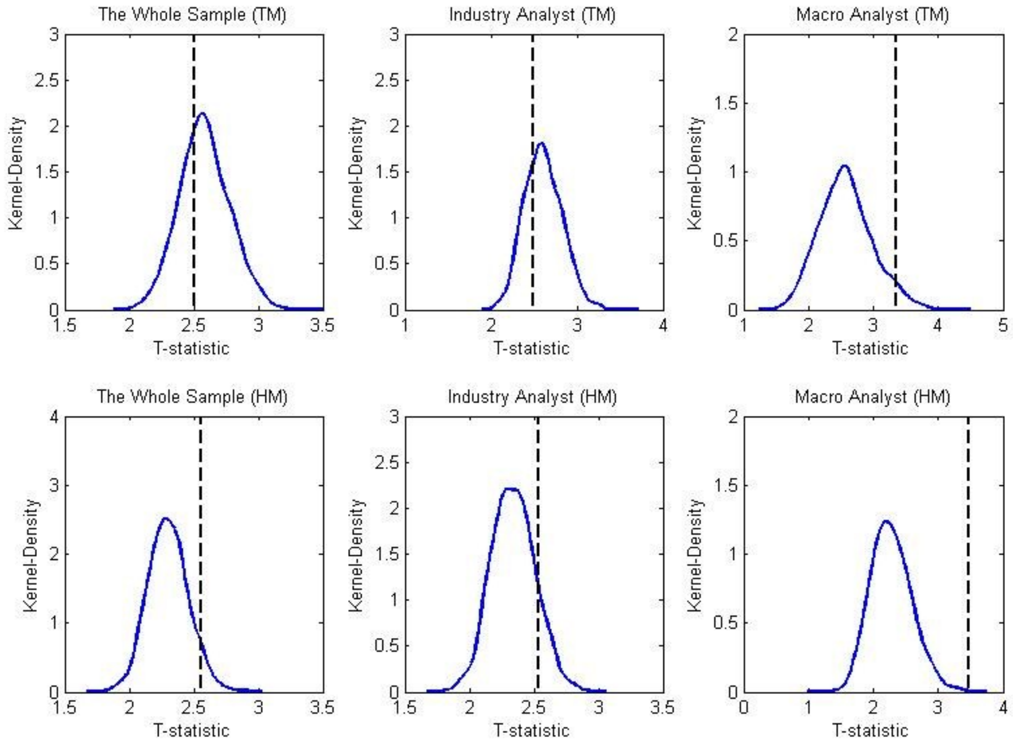

Fig.2. The 5th percentile cross-sectional t-statistics of timing coefficient.

This figure plots the 5th percentile cross-sectional t-statistics of market-timing coefficient using the TM model and the HM: actual fund vs. bootstrapped funds. The solid line is kernel density estimate based on 1000 bootstrap simulations, while the dashed line is for the actual t-statistics of alpha calculated on the real data. The graphics from left to right are for the whole sample, the industry analyst group and the macro analyst group. The top panel is for the TM model and the bottom panel is for the HM model.

This article is protected by copyright. All rights reserved.