Smart Beta, Smart Money*

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Abstract

Factor-timing strategies in the U.S. produce weak returns and are strongly correlated to the basic factor-holding strategies. We present contrasting evidence from China, where mutual funds successfully time the size factor despite a negative unconditional loading. Funds with bigger return gaps exhibit more size-factor-timing skill and outperform. Additionally, size-factor timing serves as an important channel of performance persistence, especially among high-alpha funds. Finally, we estimate fund position in different size portfolios and show that they significantly forecast size-factor returns.

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1. Introduction

The asset-pricing literature has focused on a set of priced factors that explain the cross-section of asset returns. Finding a factor with unconditionally positive average returns is one way to produce abnormal returns. Another way is to time the factor: to increase the loading on the factor when its conditional expected return is higher than average, and vice versa. Factor timing, also known as smart beta, is becoming a popular trend in the asset-management industry.

Founder of AQR Capital, Cliff Asness (2016a) concludes that timing strategies in the U.S. market produce weak returns. He also claims that factor-timing strategies are too correlated to the basic factor-holding strategies to add significant alpha. Even for the skilled institutional investors in the U.S. stock market, rare evidence exists for their aggregate factor-timing skill. In our paper, we present contrasting evidence from the Chinese stock market and show that stock mutual funds are profitably timing the size factor despite their negative unconditional factor loading. Not only are the Chinese mutual funds equipped with smart beta, but they are also serving as smart money in the stock market, as reflected by their significantly positive alpha against passive benchmarks.

Established in 1991, China's stock market has gone through rapid development and has become the second largest in the world, with a market capitalization of $5 trillion by August 2016. Carpenter, Lu and Whitelaw (2015) show that Chinese stock market price risk and other stock characteristics remarkably like investors in other large economies. Specifically, we observe that the size factor is a persistently positively priced factor in the Chinese stock market. Meanwhile, Chi (2016) finds that on one hand, Chinese retail investors in aggregate invest significantly more in small-cap stocks but still underperform the market. On the other hand, Chinese actively managed stock mutual funds outperform the market despite a significantly negative loading on the size factor. These observations together constitute a puzzle: how can a negative exposure to a significantly positively priced factor lead to outperformance, and vice versa? We address this puzzle by studying Chinese stock mutual funds' factor-timing skill.

First, we test the factor-timing skill of Chinese stock mutual funds with two factor-timing models extended from Treynor and Mazuy (1966) and Henriksson and Merton (1984). We find strong evidence of significant size-factor-timing skill of Chinese stock mutual funds both in aggregate and cross-sectionally. We find that such timing skill attributes about 50%~60% to the alphas of Chinese stock mutual funds. Our findings are in contrast to our results on U.S. stock mutual funds, which suggest little evidence for factor-timing skill.

As noted by Ferson and Schadt (1996), lagged market conditions are public information and adjustment of factor loadings based on public information does not reflect true timing skill. We address this concern by controlling for past information in our factor-timing regression. We find that Chinese mutual funds are able to change size-factor exposure based on valuable private information. That is, they are not simply adjusting factor exposures to past information. Our results stand in contrast to Frijins, Gilbert and Zwinkels (2016), who find that U.S. mutual funds adjust factor exposure to past returns rather than future returns.

We further show that the size-factor-timing skill arises from intra-period trading. We first show that the semiannually reported stock holdings of Chinese mutual funds do not exhibit size-factor-timing skill. In other words, the timing skill is orthogonal to funds' stock-picking ability at semiannual frequencies. Motivated by Kacperczyk, Sialm and Zheng (2005), we measure the impact of the unobserved actions of mutual funds by the return gap – the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. We find that funds with bigger return gaps in the past show higher size-factor-timing skill in the future, and perform better. We believe that timing the size factor is an important channel of performance attribution for Chinese stock mutual funds.

We conduct similar analyses to study the U.S. mutual funds' size-factor-timing skill. First, we analyze their aggregate factor-timing skill through a regression framework. We find no evidence for U.S. mutual funds' skill to time the size factor. Second, we analyze their cross-sectional factor-timing skill through a bootstrap simulation framework. Despite the weak evidence for some U.S. funds to show size-factor-timing skill, their performance is not far apart from the zero-skill simulation benchmark. In contrast, the Chinese funds' performance is far above the zero-skill simulation benchmark. We attribute these results to the different stages of development of these two stock markets. There is no doubt that the Chinese stock market is at an earlier stage of development. Institutional features such as a large body of trigger-happy retail investors and a not-yet-mature hedge fund space render the Chinese stock market much less competitive than the U.S. market. Faced with softer competition, Chinese mutual funds are still serving as smart money in the stock market.

Second, we study the persistence of size-factor-timing skill and its impact on mutual fund performance persistence. First, through a single sort of past fund alpha, we find evidence of performance persistence of Chinese stock mutual funds. Second, through a double sort of past fund alpha and past size-factor-timing skill, we find that fund performance is predictable by past fund alpha, but only within those funds that have significant size-factor-timing skill. We also find that size-factor-timing skill is persistent among high-alpha funds. But size-factor-timing skill of low-alpha funds has more random element.

Third, we track the asset-allocation style of Chinese stock mutual funds and use this information to forecast the size-factor returns. First, we propose a simple return-based optimization method to estimate mutual funds' asset allocation in different size cohorts. Second, we show that mutual funds' aggregate lagged position dispersion in small-cap and large-cap stocks significantly forecasts size-factor returns. Third, we show that our position estimations of funds with better timing skill exhibit stronger forecasting power to future size-factor returns. Our forecasting result is also robust for the industry-neutral size-factor returns, which control for the industry rotation. Moreover, we estimate rolling and time-varying size-beta for mutual funds portfolio and show that it has similar predictive power for size-factor returns. Both predictors produce significant forecasting power out of sample, with monthly out-of-sample R-square ranging from 3.33% to 7.23%.

Our paper contributes to several strands of the finance literature. First, our paper extends the literature on factor timing by addressing a puzzle in the Chinese stock market that involves institutional investors, retail investors, and the size factor. We show that Chinese mutual funds time the size factor profitably, unlike their counterparts in the U.S. stock market. For example, Arnott, Beck, Kalesnik, and West (2016) and Asness (2016b) both test the value-based tactical factor-timing strategies and show that they add little improvement to portfolios that already load on the value factor. Furthermore, we show that factor loading is not the whole picture, as Chinese retail/institutional investors load positively/negatively on the size factor, but still underperform/outperform the market. Moreover, successful factor timing does not necessarily require positive factor loading. Chinese stock mutual funds load negatively on the size factor, but time the size factor so well that they still manage to deliver significantly positive alphas.

Second, our paper extends the literature on mutual fund performance attribution. According to Fama (1972), fund manager skill can be subdivided into two parts: selectivity and market timing. Osinga, Schauten and Zwinkels (2016) find evidence of factor-timing ability of U.S. hedge funds. We study the Chinese mutual funds and show that they are able to generate size-factor-timing alpha by taking advantage of less sophisticated retail investors. In this respect, our results are similar to those in the U.S. stock market: U.S. hedge funds show a certain degree of factor-timing skill at the expense of less sophisticated mutual funds and retail investors. The only difference here is that in China, mutual funds are still serving the role of smart money, whereas in the U.S., mutual funds are not but hedges funds are still getting the best of the factor-timing game.

Third, our paper extends the growing literature on funds' performance persistence. Carhart (1997) shows that the one-year momentum of stock prices drives the hot-hand effect of U.S. mutual funds. Cao, Chen, Liang and Lo (2012) show that U.S. hedge funds' ability to time the market liquidity contributes to their total performance persistence. Jiang, Shen, Wermers and Yao (2016) argue that the performance persistence of U.S. stock mutual funds only exists in those funds that invest heavily in high-information-intensity stocks. Our paper not only establishes the performance persistence of Chinese stock mutual funds, but also shows that the size-factor timing is an important aspect of performance persistence. On one hand, we observe stronger performance persistence among funds that show more skill in timing the size factor. On the other hand, we show that size-factor-timing skill is only persistent among high-alpha funds.

Finally, our paper extends the literature on the relationship of institutional investors' time-varying characteristic preference and asset-pricing anomalies. Gompers and Metrick (2001) show that demand shifts by institutions in particular influence security prices. They also show that institutional investors in U.S. stock market prefer larger stocks and the rapid increase of ownership in the last 20 years may account for the poor performance of small stocks after 1983. Jiang (2009) shows that the tendency of institutions to trade in the direction of intangible information exacerbates price overreaction, thereby contributing to the value premium. Lou (2011) finds that the flow-driven return effect can partially explain stock price momentum. Arkbas, Armstrong, Sorescu and Subrahmanyam (2015) find that aggregate flows to mutual funds appear to exacerbate cross-sectional mispricing, particularly for growth, accrual, and momentum anomalies. In contrast, hedge fund flows appear to attenuate aggregate mispricing. We propose a simple fund-position proxy based on daily fund returns to capture fund holdings' size dispersion. We show that this proxy significantly forecasts subsequent size-factor returns. Again, this shows that the mutual funds in China are still serving the role of smart money: their investment preference on the size-factor generates substantial amount of alpha for their performance.

The rest of our paper is organized as follows. Section 2 describes data and methodology. Section 3 evaluates the size-factor-timing skill of Chinese stock mutual funds. Section 4 studies the persistence of size-factor-timing skill and its influence on fund performance persistence. Section 5 investigates the forecasting power of funds' position in different size portfolios to subsequent size-factor returns. Section 6 conducts robustness checks. Section 7 concludes.

2. Data and Methodology

2.1 Chinese stock market data

We collect Chinese A-share stock market data from WIND®. We cover all publicly listed stocks in Shanghai Stock Exchange and Shenzhen Stock Exchange, which comprises 2,891 stocks as of December 2015. This is also the stock universe for the investment of Chinese stock mutual funds in our sample. Our dataset includes but is not limited to daily data of stock returns, trading status, market capitalization, high, low, open, close, value-weighted average price, and major index returns (SSE50, CSI300, and CSI500), annual data of book value at the end of each June, industry classifications following the global industry classification standard (GICS), and IPO dates.

We further construct the common risk benchmarks using the Chinese stock data. We discuss details for our procedure and summary statistics for the factors in Table 1. We report two sets of sample periods. The whole sample period is from Jan 1999 to Dec 2015. The sub-sample period is from Jan 2003 to Dec 2015. We use the sub-sample period to study Chinese stock mutual funds because before 2003 there are too few funds to form a meaningful sample. Size factor is one of the most significant factors in the Chinese stock market. The SMB factor has an average monthly return of 0.84% (t=2.70) in our whole sample period. Also in figure1, we have a plot of the time series returns of the SMB factor.

2.2 Chinese mutual fund data

The actively managed stock mutual funds in our sample invest primarily in the A-share stock market. We collect 535 stock mutual funds' data from the sample period of Jan 1998 to Dec 2015. Before Aug 2014, the Chinese Securities Regulatory Commission (CSRS) required stock mutual funds to invest at least 60% of their total asset value in the stock market. But after that the bottom constraint has been raised to 80%, which caused more than half of the stock mutual funds to change their fund type to hybrid stock fund. The hybrid stock funds invest mostly in the Chinese stock market but have no position constraint. In this study, we include the 420 stock mutual funds established before Aug

2014 (although many of these funds become hybrid stock fund after Aug 2014) and 115 stock mutual funds established between Aug 2014 and Dec 2015 (these 115 stock funds are required to invest more than 80% of their total asset in the stock market). Our data set is free of incubation bias and survivorship bias. All open-end funds must publicly report their establishment to CSRC and all closed-end funds trade on the stock exchange. We collect both alive and defunct mutual funds. As can be seen from Table 2.B, actively managed stock mutual funds represent a substantial portion of the Chinese stock market. For example, in 2007, their aggregate holdings represented 16.6% of the Chinese stock market capitalization.

For each fund, we collect daily reported net asset value (NAV) data for open-end funds and weekly reported NAV data for closed-end funds. Return calculations are based on the funds NAV adjusted for dividend payout. We also collect data for fund characteristics, which include but is not limited to total net asset value (TNA), fund expense ratio (custodian fee and management fee), annual turnover ratio and percentage of institutional and retail investors in the fund holding structure. All the summary statistics for these fund characteristics in subsample period: Jan 2003 to Dec 2015 are reported in Table 2.A.

For the subsample period from March 2003 to December 2015, we collect each fund's stock-holdings data. Since the beginning of 2003, all stock mutual funds are required to disclose their top-10 stock holdings in quarterly reports, and their entire holdings in semiannual reports. Quarterly reports disclose fund holdings at the end of March, June, September, and December. Semiannual reports refer to interim and yearend reports. Interim reports disclose fund holdings at the end of each June. Year-end reports disclose fund holdings at the end of each December. We collect quarterly holdings data from March 2003 to December 2015, for a total of 52 quarters. We collect semiannual holdings data from June 2003 to December 2015, for a total of 26 reporting periods. WIND has a unique advantage in linking holdings data directly to each fund. So matching stock holdings to a mutual fund is convenient.

It is worth noticing that Chinese stock mutual funds have extremely high turnover and exhibit a large cross-sectional variation. They have a median turnover of 406% and an average turnover of 500% in the period 2003-2015. The standard deviation is as high as 340%. In contrast, the U.S. stock mutual funds have a much lower turnover. Over the period 1984-2003, Kacperczyk, Sialm and Zheng (2005) show that the U.S. stock mutual funds have a median turnover of 65% and a mean turnover of 88%. This is consistent with the evidence that Chinese stock mutual funds engage in factor timing and change their factor loadings somewhat frequently. We also extend our fund samples to hybrid funds and find similar results. We discuss those results on hybrid funds in the Appendix.

2.3 U.S. mutual fund data

We follow the procedure taken by Pastor, Stambaugh, and Taylor (2016) in constructing our U.S. mutual fund sample. In particular, we combine CRSP and Morningstar data to obtain a sample of U.S. domestic equity mutual funds covering the 1980-2014 period. We study the net returns of our U.S. fund sample, consistent with what we do with our Chinese fund sample.

2.4 Factor-timing model

We build a return-based factor-timing model, based on the frameworks of Treynor and Mazuy (1966) and Henriksson and Merton (1981). The framework of Treynor and Mazuy (TM) model is based on the capital asset pricing model (CAPM). The idea behind the framework of TM model is that the fund manager will adjust market beta $\beta_{i,t}$ in month *t+1* on forecasted market movements. A first-order Taylor series expansion is used to express market beta as a linear function of the forecasted market returns.

$$\beta_{i,t} = \beta_i + \gamma_i E(MKT_{t+1}|I_t), \tag{1}$$

where γ_i is the coefficient that captures the timing skill and $E(MKT_{t+1}|I_t)$ is the manager's forecast of the market return given the information set I_t in period t. So by substituting equation (1) into CAPM model results in the TM market-timing model:

$$R_{i,t+1} = \alpha_i + \beta_i MKT_{t+1} + \gamma_i MKT_{t+1}^2 + \varepsilon_{i,t+1}. \tag{2}$$

The Henriksson and Merton (HM) propose a parametric model that estimates timing skill by assuming the manager has two betas: one in up market and the other in down market.

$$R_{i,t+1} = \alpha_i + \beta_i MKT_{t+1} + \gamma_i I(MKT_{t+1} > 0)MKT_{t+1} + \varepsilon_{i,t+1}. \tag{3}$$

We focus on the factor timing skill of mutual fund managers, which is the skill of a manager to adjust the factor exposure for a specific factor based on a forecast of the factor condition. So we extend the TM and HM model to the following versions:

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{j=1}^{J} \gamma_{i,j} f_{j,t+1}^2 + \varepsilon_{i,t+1}, \quad (4)$$

$$R_{i,t+1} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j} f_{j,t+1} + \sum_{j=1}^{J} \gamma_{i,j} I(f_{j,t+1} > 0) f_{j,t+1} + \varepsilon_{i,t+1}. \quad (5)$$

We use the commonly used risk benchmarks for Chinese stock market: $f_{1,t+1} = MKT, f_{2,t+1} = SMB, f_{3,t+1} = HML, f_{4,t+1} = MOM.$ We do a blanket investigation on all factor-timing evaluations on the Chinese stock mutual funds. We include results in Table B in the Appendix. Because we only discover significant timing skill in the size factor, we focus on the SMB factor in factor-timing regressions (4) and (5) in the main body of our paper.

2.5 Fund-position estimation

We develop a new and simple return-based model to estimate fund position in different size portfolios. The basic framework of our model is to construct an index return based on different size portfolios and maximize the R-square between the mutual fund return series and the composite index return series. The optimized weights of different size portfolios in the composite index are the estimated fund positions in different size portfolios.

First, we construct monthly formed size portfolios based on the market-cap of the stocks at the end of last month. Stocks with market-cap in the top 30^{th} percentile of all market-cap for publicly listed Chinese A stocks are classified as “big”, while stocks with market-cap in the bottom 30^{th} percentile are classified as “small”. Stocks with market-cap in the middle 40 percentiles (30^{th} to 70^{th} percentile) are classified as “medium”. We then calculate value-weighted daily returns for each portfolio: R_{Big}, R_{Medium} and R_{Small} using monthly market-cap data. We solve the following optimization problem with each mutual fund’s daily net return $R_{MF,t}$:

$$Min \quad \left\| R_{MF,t} - R_{composite,t} \right\|_2^2 = \frac{1}{T} \sum_{t=1}^{T} \left(R_{MF,t} - R_{composite,t} \right)^2,$$

$$R_{composite,t} = POS_1 * R_{Big,t} + POS_2 * R_{Medium,t} + POS_3 * R_{Small,t} \ ,$$

$$\text{s.t } \sum_{i=1}^{3} POS_i \leq 1 \quad \text{and} \quad POS_i \geq 0 \ , \tag{6}$$

where the optimized parameters: POS_1, POS_2 and POS_3 are the mutual funds' estimated positions in different size portfolios.

Our optimization method has several advantages. First, we only use the daily publically reported return data for each fund, so our estimation is timely and easy to implement. Second, we avoid the multi-collinearity problem of running a multiple regression on various size-portfolios' return series. Though, we did try this multiple-regression-estimation approach and found similar results. We are happy to provide those results to interested readers. Third, the constraints we incorporate in our optimization framework help us produce economically meaningful estimations. We constrain the portfolio weights to sum up to less than one, instead of one, because Chinese mutual funds vary their cash weights quite a lot. On average, they hold 80% of fund assets in stocks during our sample period.

3. Chinese Stock Mutual Funds' Size-Factor-Timing Skill

In this section, we first evaluate Chinese stock mutual funds' size-factor-timing skill, both in an aggregate regression framework and in a cross-sectional bootstrap framework. Second, we study fund characteristics that help determine their factor-timing skill. Third, we distinguish the concepts of factor timing from factor reaction. Fourth, we study the relationship between funds' return gap and size-factor-timing skill. Finally, we conduct similar analysis for the size-factor-timing skill of U.S. stock mutual funds.

3.1 Aggregate size-factor-timing skill

First we test the aggregate performance of equal-weighted (EW) and value-weighted (VW) stock mutual fund portfolios with CAPM, Fama and French's (1993) three-factor model (FF3F), and Carhart's four-factor model (FF3F+MOM). Variants of the flowing time-series regression are used by these three models:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_{mf,t} \tag{7}$$

The value-weighted (VW) portfolio is weighted by fund AUM at the beginning of each month, and the equal-weighted (EW) portfolio weights funds equally each month.

Table 3.A shows estimates of regression (7) for monthly net returns of Jan 2003 to Dec 2015 on EW and VW portfolios of all the 535 stock funds in our sample. Consistent with the finding of Chi (2016), both EW and VW fund portfolios produce statistically and economically significant alphas. For example, the VW fund portfolio's net returns have an annual CAPM intercept of 5.16% (t=1.75), a FF3F intercept of 9.91% (t=4.89) and a FF3F+MOM intercept of 9.28% (t=4.97). It is also interesting to find that both EW and VW portfolios load significantly negative on SMB and HML and significantly positive on MOM. The VW fund portfolio loads –0.15 (t=–4.44) and EW fund portfolio loads –0.11 (t=–3.43) on SMB. It is in sharp contrast from Fama and French's (2010) results showing that U.S. stock mutual funds load significantly positively on SMB with a loading of 0.07 (t=7.78) for the VW portfolio during period Jan 1984 to Sep 2006. In aggregate, Chinese stock funds invest more in large growth stocks and tend to chase past winners. Mutual funds in China are a good representation for institutional investors. As Chi (2016) shows, Chinese institutional investors in aggregate exhibit similar loadings on these factors. Therefore, the remaining retail investors in China in aggregate invest more in small-cap stocks with a value and contrarian focus.

Next, we study the factor-timing skill of Chinese stock mutual funds. We run regressions (4) and (5) with the size-factor-timing specification. The coefficient and t-statistic of γ measure the funds' timing skill.

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma I(SMB_t > 0)SMB_t + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_{mf,t} \quad (8)$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma SMB_t * SMB_t + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_{mf,t} \quad (9)$$

We find that Chinese stock mutual funds in aggregate possess significant size-factor-timing skill. In Table 3.B and 3.C, we show estimates of regressions (8) and (9) for monthly net returns of EW and VW portfolios of 535 stock funds in our sample. Both EW and VW portfolios exhibit statistically and economically significant size-factor-timing skill under both HM and TM models. VW portfolio's size-factor-timing coefficient is 0.22 (t=2.12) under the HM_FF3F model and 0.27 (t=2.87) under the HM_FF3F+MOM model. To gain intuition on the HM coefficient 0.27 of $I(SMB_t > 0)SMB_t$, we compare it with the SMB_t beta of the VW portfolio under FF3F+MOM model, which is –0.15. This indicates that when monthly size factor return is positive, stock mutual funds' beta on SMB increases by 0.27, about 180% of the average magnitude of SMB_t beta. Similarly, VW portfolio's size-factor-timing coefficient is 0.85 (t=2.56) under the TM_FF3F model and 1.25 (t=3.47) under the TM_FF3F+MOM model. This indicates that when size factor return is one standard deviation (4.83%, Table 1) above its monthly mean, mutual funds' SMB_t beta increases by 0.06 (1.25*4.83%), which equals 40% of the average magnitude of SMB_t beta of 0.15.

We also find that alphas of both EW and VW portfolios are diluted after controlling for the conditional beta on the size factor under both models. For example, the VW portfolio's net returns exhibit an annual HM_FF3F intercept of 4.93% (t=1.60) and a HM_FF3F+MOM intercept of 3.90% (t=1.10) in Table 3.B, compared with a FF3F intercept of 9.91% (t=4.89) and a FF3F+MOM intercept of 9.28% (t=4.97) in Table 3.A. That is, incorporating the size-factor timing term has helped explain away about 50.25% (57.65%) of the funds' FF3F (FF3F+MOM) alpha. We conclude that the significant size-factor-timing skill of Chinese stock mutual funds contributes a substantial portion to their performance.

3.2 Cross-sectional size-factor-timing skill: bootstrap analysis

We now describe the bootstrap procedure used to analyze the cross section of size-factor-timing skill's distribution. The bootstrap analysis helps us answer the question whether the result of size-factor-timing skill is due to pure luck. Our bootstrap procedure is similar to that of Kosowski (2007), Fama and French (2010) and Cao, Chen, Liang and Lo (2012).

We randomly resample data to generate hypothetical funds that have the same factor loadings as the actual funds but with zero timing skill. Then we analyze how the simulated timing coefficients differ from the actual timing coefficients. We focus on the t-statistic of the timing coefficient for our analysis, because of its favorable sampling properties in bootstrap analysis. We eliminate funds with less than 12 reported monthly returns. As a result, our sample covers 444 funds from the period Jan 2003 to Dec 2015. Now we discuss details of each step of our bootstrap procedure.

1. Estimate the size-factor-timing model for fund p using regression (8) (HM) and regression (9) (TM), and store the estimated coefficients $\{\alpha_p, b_p, \gamma_p, ...\}$ as well as the time

series of residual $\{\varepsilon_{p,t}, t = 0, \dots T_p\}$, where T_p is the number of monthly observations for fund p.

2. Resample the residuals with replacement and obtain a randomly resampled residual time series $\{\varepsilon_{p,t}^{b}\}$, where b is the index for bootstrap iterations. Then we generate monthly returns for a pseudo fund that has no size-factor-timing skill (i.e. $\gamma_p = 0, t_\gamma = 0$) by construction, that is, we set the coefficient on the size-factor-timing term to be zero in the HM and TM models.

3. Estimate the size-factor-timing model (8) and (9) using the pseudo-fund returns from step 2, and store the estimation of the timing coefficient and its t-statistics. Since the pseudo fund has a true γ of zero by construction, any non-zeros timing coefficient and t-statistics comes from sampling variance.

4. Complete steps 1-3 across all the sample funds, so that we can observe the cross-sectional statistics of the t-statistics for the timing coefficients across all of the sample funds.

5. Repeat steps 1-4 for 5,000 times to generate an empirical distribution for cross-sectional statistics of t-statistics for the pseudo funds. We calculate its empirical p-value for a certain cross-sectional percentile as the frequency that the values of the bootstrapped t-statistics for the pseudo funds from 5,000 simulations exceed the actual value of the t-statistic.

In Table 4.A and Table 4.B, we report the empirical p-values corresponding to the t-statistics of size-factor-timing coefficient under the FF3F version of HM and TM models. We find widespread cross-sectional evidence of size-factor-timing skill in Chinese stock mutual funds. Specifically, the t_γ's for the top 1%, 3%, 5% and 10% of funds are 4.61, 3.85, 3.68 and 3.20 for the FF3F version of HM model. It is striking to find that under both timing models, the majority of funds exhibit significant timing skill. The cumulative probability graph offers a visual representation of the table. We see that for the majority of stock funds (top 95%), the actual timing-skill curve first-order-stochastically-dominate the simulated timing-skill curve. In other words, the cross-sectional distribution of Chinese stock funds' size-factor-timing skill far outperforms the zero-timing-skill pseudo sample. We conclude that cross-sectional size-factor-timing skill widely exists in Chinese stock mutual funds, which can't be attributed to pure luck.

3.3 Determinants of funds' size-factor-timing skill

After having established the fact that Chinese stock mutual funds possess significant size-factor-timing skill, we now turn to the question on which fund characteristics are related to such timing skill. We quantify size-factor-timing skill by the t-statistic of the size-factor-timing coefficient $t(\gamma)$. We estimate $t(\gamma)$ under the FF3F and FF3F+MOM versions of regression (8) and (9). We then run a regression with explanatory variables including a fund's size, age, expense ratio, percentage of institutional ownership, turnover ratio and closed-end status.

$$t\,(\gamma)_i = \alpha_i + \beta_1 \log(TNA)_i + \beta_2 log(Age)_i + \beta_3 Exp_i + \beta_4 Ins\ pct_i + \beta_5 Turnover_i + \beta_6 Close\ end_i + \varepsilon_i \tag{10}$$

We show in Table 5 that size-factor-timing skill is more significant for funds that are smaller, older and with higher turnover ratio. Our findings can be intuitive. We believe that these characteristics fit the profile of an active fund with skill to identify time-varying investment opportunities. Smaller funds are more likely to buy small stocks, which are more likely to be subject to information asymmetry. High-turnover funds are more likely to make use of timely private information or mispricing opportunities. Older mutual funds have more experience in timing the factor and more connections in acquiring private information.

3.4 Factor timing vs. factor reaction

It is important to distinguish factor timing from factor reaction. If a factor's returns were serially autocorrelated, their values in month *t* would contain information from prior months. Thus a fund manager may adjust factor exposure based on lagged values of factor returns. As noted by Ferson and Schadt (1996), lagged market conditions are public information and adjusting fund betas based on public information does not reflect true timing skill. In order to distinguish size-factor timing from size-factor reaction, we decompose the factor returns by estimating the following two regressions, in which both size-factor-timing terms and size-factor-reaction terms are included:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma\varepsilon_t SMB_t + \beta SMB_{t-1} SMB_t + s_{mf} SMB_t + HML_t + m_{mf} MOM_t + e_t, \tag{11}$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma I(\varepsilon_t > 0)SMB_t + \beta I(SMB_{t-1} > 0)SMB_t + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + e_t \quad (12)$$

In these two regressions, SMB_{t-1} is the one month lagged size factor return and represents a predictable component of size factor, while ε_t is the innovation term in the size factor's AR (1) process. The coefficient γ measures the size-factor-timing skill, whereas the coefficient β measures the size-factor reaction. If a manager only reacts to past factor conditions, we expect his factor-timing coefficient γ to be insignificant once we take factor reaction (β) into consideration.

In Table 6.A, we report the results of AR (1) process for different versions of size factor returns. We show that for all size factors the coefficient of lagged returns are not significant. Size factor return series are stationary with ADF-test's p-values close to zero. But we can't rule out the possibility that during some periods, the size factor returns are significantly serially correlated. So it is still important to carry out regressions (11) and (12). In Table 6.B, we show that the coefficient of size-factor-timing skill (γ) remains significant after controlling for size-factor reaction (β). For example, in HM_FF3F+MOM model, the timing term's coefficient is 0.26 (t=2.55), while the reaction term's coefficient is only 0.07 (t=1.05). Similarly, in TM_FF3F+MOM model the timing term's coefficient is 1.42 (t=3.78), while the reaction term's coefficient is only –0.17 (t=–0.29). Overall, we conclude that Chinese stock fund managers have skill to predict future factor conditions, instead of simply reacting to past public information.

3.5 Return Gap and Size-Factor Timing

In this section, we try to answer the question whether funds' size-factor-timing skill arises from selecting and holding stocks or from intra-period trading. Is it possible that some individual stocks themselves have smart time-varying size beta that helps the funds holding these stocks to exhibit size-factor-timing skill? Moreover, if it arises from intra-period trading, we hypothesize that size-factor timing should be an important part of the value-creating interim trades of funds in China. Thus we try to find the relationship of size-factor timing and return gap, which is a direct measure of the value added by the fund manager relative to the previously disclosed holdings. (Kacperczyk, Sialm and Zheng (2005))

3.5.1 Size-factor-timing skill of the semiannual holding portfolio

First, we try to evaluate the performance, especially the size-factor-timing skill of the semiannual portfolio. At the end of each semiannual period from June 2003 to December 2015, we construct a stock portfolio (“All Holdings”) that aggregates stock holdings of all the stock funds. We appropriately adjust the portfolio’s value weights monthly to create a buy-and-hold return series for the six months following the portfolio formation. We then paste the six-month return series together to create a longer time series of monthly returns. This portfolio tracks the aggregate stock funds’ stock holdings every six months without any lag. In Table 7.B, we show estimates of regressions (8) and (9) for monthly net returns of the semiannual portfolios of the 535 stock funds in our sample. The semiannual portfolio does not exhibit significant size-factor-timing skill under either HM or TM models. For example, the semiannual portfolio’s size-factor-timing coefficient is insignificantly away from zero (0.02, t=0.22). This evidence shows that the size-factor-timing skill arises from intra-period trading, and is orthogonal to the stock picking ability.

3.5.2 Return gap and size-factor timing

Next, motivated by the result of Kacperczyk, Sialm and Zheng (2005) that the return gap predicts fund performance, we test our hypothesis: Funds with bigger return gap have higher size-factor-timing skill, and thus perform better. First, we calculate the return gap of each mutual fund each month by subtracting the monthly net return on each fund’s portfolio that invests in the previously disclosed fund holdings from the reported monthly net fund return. At each month-end, we sort mutual funds into quintile portfolios based on their past 12 months’ return gap and hold each portfolio for one month. We require funds to have the past 12 months’ return gap data to be included in our sorting procedure. We then report the size-factor-timing coefficient: γ and its t-statistic $t(\gamma)$ estimated with the FF3F version of regression (2) (HM) and (3) (TM) of each equal weighted mutual fund portfolio in the time periods of July 2003 to Dec 2015. We show in Table 8 that fund’s past return gap positively forecasts future size-factor-timing skill. For example, the size-factor-timing coefficient for the top-return-gap quartile is 0.33 (t=2.95), whereas the coefficient for the bottom-return-gap quartile is 0.14 (t=1.15) under the HM_FF3F model.

Moreover, we run the following two cross-sectional regressions: regressing t-statistic of the size-factor-timing coefficient $t(\gamma)$ on explanatory variables including a fund’s return gap, size, age and turnover ratio.

$$t\ (\gamma)_i = \alpha_i + \beta_1 Return\ Gap_i + \varepsilon_i \tag{15}$$

$$t\ (\gamma)_i = \alpha_i + \beta_1 Return\ Gap_i + \beta_2 log(TNA)_i + \beta_3 log(Age)_i + \beta_4 Turnover_i + \varepsilon_i \tag{16}$$

Table 9 reports the results of the whole sample cross-sectional regressions that analyze the effects of return gap on size-factor-timing skill. The coefficient of the return gap is 0.62 (t=6.03) with R-square of 7.61% measured by $t\ (\gamma)$ under HM_FF3F model in regression (15). This means that 1% increase in mutual fund's average monthly return gap corresponds to a 0.62 increase in the t-statistics of the $t\ (\gamma)$. The effect of return gap on size-factor-timing skill still exists after we control for the fund characteristics that significantly affect fund size-factor-timing skill in regression (16). The coefficient of the return gap is 0.59 (t=5.80) with R-square of 15.84% measured by $t\ (\gamma)$ under HM_FF3F model.

All these results suggest that the smart size beta serves as an important channel of how return gap predicts fund performance. We show that the size-factor timing skill, although can't be observed through fund holdings, persistently adds value to the fund performance through intra-period trading. Also under a less efficient market environment, such factor-timing skill can cover the hidden costs, such as trading costs, agency costs, and negative investor externalities. We conclude that factor timing can serve as an important proportion of the unobserved actions that help predict future fund performance.

3.6 Comparison with U.S. Mutual Funds

In this section, we offer a comparison of our results with results on the U.S. stock mutual fund sample. First, in Table 10.A, we show that consistent with the literature, U.S. mutual funds exhibit no outperformance against the market and passive benchmark. In the value-weight specification, we actually observe significant underperformance using funds' net returns. This sharp contrast between the two countries' mutual fund performance has been documented in details by Chi (2016). Second, we show in Table 10.B and 10.C that U.S. mutual funds in aggregate exhibit no size-factor-timing skill. Third, we show in Table 10.D that U.S. mutual funds show some, but very weak evidence for size-factor-timing skill. It is visually striking to compare the cross-sectional-distribution graphs in Table 10.D and Table 4. We see far more Chinese stock funds show far greater size-factor-timing skill, against a zero-skill simulated pseudo sample.

To some extent, we anticipate these results because the U.S. stock market is far more competitive than the Chinese stock market. The mutual funds in the U.S. are competing against many other institutional investors, and few retail investors. In contrast, mutual funds in China are competing against many retail investors who are less sophisticated. Over 80% of the stock market's trading volume is still generated by retail investors in China, whereas institutional investors in the U.S generate over 90% of the stock market's trading volume. This stark difference in the two markets inevitably leads to different levels of competition, which in turn leads to the sharp contrast in the performance of the mutual funds in the two countries.

4. Size-Factor Timing and Performance Persistence

From last section's results, we understand that size-factor-timing skill adds positive economic value to fund performance. Now we turn our attention to the persistence of such skill. We employ out-of-sample tests to study the effects of size-factor-timing on fund performance and the persistence of size-factor-timing skill.

4.1 Single sort by past alpha and size-factor-timing skill

We first use a single-sort approach to study performance persistence. At each month-end, we sort funds into quintile portfolios based on their past 12-month CAPM (FF3F and FF3F+MOM) alpha and hold them for one month. We then report each portfolio's alpha and t-statistic in Table 11.A. Funds in the top past-alpha quintile significantly outperform those in the bottom quintile by 0.50% (t=2.75) in CAPM alpha, 0.46% (t=4.00) in FF3F alpha, and 0.37% (t=3.09) in FF3F+MOM alpha.

We then sort funds into quintile portfolios based on past 12-month size-factor-timing skill, measured by $t(\gamma)$ estimated in regression (8). We report each portfolio's CAPM (FF3F and FF3F+MOM) alpha and t-statistic in Table 11.B. Results in Table 11.B suggest that past size-factor-timing skill is not significantly related to future fund performance. For example, the difference in alphas between the top and bottom portfolios is 0.10% (t=0.80) under CAPM. The insignificant relationship between size-factor-timing skill and subsequent fund performance suggests that not all funds can persistently time the size factor successfully. In unreported results, we measure past alpha and past size-factor-timing skill using 24 to 36 months window and find similar results.

4.2 Double sort by past alpha and size-factor-timing skill

We now turn to analysis based on double-sorted fund portfolios to study the interaction between fund alpha and size-factor-timing skill. At each month-end, we independently sort funds by past alpha and size-factor-timing skill into tertile portfolios. Funds in the top 20th percentile are classified as "high", while funds in the bottom 20th percentile are classified as "low". Funds in the middle 60 percentiles (20th to 80th percentile) are classified as "medium". This results in 9 fund portfolios.

To ensure robustness of inference, past alpha are estimated using past 12-month raw returns from the CAPM, FF3F, and FF3F+MOM models respectively. Panels A, B, C of Table 12 report the performance of the double-sorted fund portfolios under these three different past alpha measures. The patterns under all three models are similar. We focus on Table 12.B, with FF3F alpha as the performance measure. First, for funds in the low size-factor-timing tertile, the monthly alpha difference between the top and bottom past-alpha tertile is 0.14% (t=0.68). There is no performance persistence among low size-factor-timing skill funds. As we move to the funds with higher size-factor-timing skill, the performance persistence becomes significant. Among funds in the top size-factor-timing tertile, the top past-alpha tertile outperforms the bottom past-alpha tertile by 0.80% (t=4.65) per month.

For funds in the bottom past-alpha tertile, the performance difference between the top and bottom past size-factor-timing tertiles is –0.38% (t=–2.39). That is, the size-factor-timing skill quickly mean reverts among low-alpha funds. Consequently, timing the size factor is a costly behavior for low-alpha funds. For funds in the top past-alpha tertile, the performance difference between the top and bottom past size-factor-timing tertile is 0.28% (t=1.89). That is, the size-factor-timing is persistent within the high-alpha funds.

In summary, size-factor-timing is a very useful performance proxy to help us understand mutual funds' performance persistence. On the one hand, we see no persistence among low-skill funds, measured by either past alpha or size-factor-timing skill. On the other hand, we see strong persistence in the highest-performing funds, in terms of both fund alpha and size-factor-timing skill. When these two dimensions of fund performance are combined together, we have arrived at a very strong indicator for future fund performance. The funds in the top past-alpha tertile and top size-factor-timing tertile deliver an FF3F alpha of 1.27% (t=6.47) on average in the following month, or 15.24% annually. Their outperformance is both statistically significant and economically large for mutual fund investors. In unreported results, we measure past alpha and past size-factor-timing skill using 24 to 36 months window and find similar results.

5. Forecast Size-Factor Returns with Estimated Fund Positions

Now that we know Chinese stock mutual funds can profitably time the size factor, we should expect that the mutual fund positions have pricing implications for the size factor. In this section, we propose a simple return-based fund-position estimate and show that it significantly forecasts the size factor's future returns. We also estimate the standard time-varying size-beta for mutual funds portfolio and show that it exhibits similar predictive power.

5.1 Forecast general size-factor returns

As discussed in detail in subsection 2.5, we use each fund's daily net returns to estimate its monthly position in large-cap, mid-cap, and small-cap stocks from Jan 2003 to Dec 2015. Next, we aggregate each fund's positions into the equal-weighted (EW) and value-weighted (VW) positions in different size portfolios. Table 13.A reports the p-values of the ADF test for the EW and VW monthly estimated fund positions in different size portfolios. In order to avoid spurious regression, we compute the fund-position estimator to be the difference between a fund's position in big stocks and its position in small stocks. Next, we use our estimated aggregate EW and VW position dispersion in small-cap stocks and large-cap stocks (*SMB_pos*) in month *t* to forecast different versions of size factor returns (*SMB_FF, SMB_50, SMB_30,* and *SMB_20*[4]) in month *t+1*. We establish the forecasting regressions as follows:

$$SMB_{t+1} = \alpha_{mf} + P_{mf} SMB\_pos_t + \varepsilon_{t+1} \ , \tag{13}$$

$$SMB_{t+1} = \alpha_{mf} + P_{mf} SMB_{pos_t} + b_{mf}(Rm_{t+1} - Rf_{t+1}) + h_{mf} HML_{t+1} + m_{mf} MOM_{t+1} + \varepsilon_{t+1}. \tag{14}$$

Table 13.B reports results for regression (13), as well as regression (14) when we control $R_m - R_f$, *HML* and *MOM* factors in month *t+1*. We show that out estimated fund position in different size portfolios has significant forecasting power to subsequent size factor's returns. For example, for the Fama-French *SMB* factor, the slope of the *SMB_pos*

[4] SMB_FF is the Fama-French version of the size factor. SMB_50/ SMB_30/SMB_20 is the value-weighted return difference between the smallest 50%/30%/20% of stocks and the largest 50%/30%/20% of stocks.

term in regression (13) is 0.028 (t=2.73) with the EW fund portfolio. The standard deviation of the *SMB_pos* is 29.78%. So a one-standard-deviation increase of the *SMB_pos* of the EW fund portfolio leads to a 0.83% increase in next month's size-factor return. The forecasting power persists after we control for $R_m - R_f$, *HML* and *MOM*, as the slope of the *SMB_pos* becomes 0.021 (t=2.05). We observe even stronger forecasting power for size factors constructed with more extreme cutoffs. For example, for the monthly-rebalanced *SMB_20* factor, the slope of the *SMB_pos* is 0.063 (t=3.09).

Next, we directly sort the months (*t*) from Jan 2003 to Dec 2015 based on the magnitude of the monthly estimated *SMB_pos* for the EW fund portfolio into four groups. In each quartile (40 months), we report the average monthly size-factor returns in the next months (*t+1*) in Table 13.C. The average subsequent monthly size-factor returns of the top *SMB_pos* quartile is 2.57 % (t=4.16), whereas the average subsequent monthly size-factor returns of the bottom *SMB_pos* quartile is –1.34% (t=–1.53). The difference between these two size-factor average returns is 3.91% (t=3.25).

Last but not least, we analyze the cross-sectional variation of funds with different levels of size-factor-timing skill. At each month-end, we sort stock funds into quartile portfolios based on their past timing skill $t(\gamma)$. In each quartile portfolio, we follow the same procedure to compute *SMB_pos* for the EW quartile portfolio. Next, we run forecasting regressions (13) and (14). We show in Table 13.D that mutual funds exhibit large cross-sectional variation in forecasting size-factor returns. For example, the coefficient of the forecasting regression for the top-timing-skill quartile is 0.04 (t=2.91), whereas the coefficient for the bottom-timing-skill quartile is 0.02 (t=1.59). We also discover that the cross-sectional variation is larger when we forecast size-factor returns constructed with more extreme cutoffs. For example, for the *SMB_20* factor, the coefficient of the forecasting regression for the top-timing-skill quartile is 0.08 (t=3.85), while the coefficient for the bottom-timing-skill quartile is 0.04 (t=1.79). These results are intuitive: funds that are better at timing the size factor in aggregate should also forecast the size-factor returns better.

5.2 Forecast industry-neutral size-factor returns

A potential concern of this result is that the forecasting power arises from the industry rotation and mutual funds are actually trying to time the industry returns instead of size-factor returns. To address this concern, we sort stocks by their market cap and B/M ratios within each of the 24 industries classified by the global industry classification standard (GICS), and then value weight stock returns across the industry to get the industry-neutral factor returns. So every industry should be represented approximately equally in the small- and big-size portfolios as well as the low- and high- B/M portfolios. Empirically, the sorting procedure does not dramatically alter the size factors. For example, *SMB_FF_N* has an average monthly return of 0.62% and a standard deviation of 3.58%, compared with 0.87% and 4.83%, respectively, for *SMB_FF*. Although the magnitude in return and variance of the industry-neutral factors are smaller, the correlation between the two size factors, 0.94, is fairly high. Next, we use our estimated aggregate EW and VW position dispersion in industry-neutral small and big size portfolios (*SMB_pos_N*) in month *t* to forecast different versions of industry-neutral size factor returns (*SMB_FF_N*, *SMB_50_N*, *SMB_30_N*, and *SMB_20_N*) in month *t+1*. As shown in Table 14.B, the forecasting power of the size factor still holds after controlling for the industry rotation. For example, for the industry-neutral Fama-French *SMB* factor, the slope of the *SMB_pos_N* term in regression (13) is 0.014 (t=1.97) with the EW fund portfolio. The standard deviation of the *SMB_pos_N* is 22.19%. So a one-standard-deviation increase of the *SMB_pos_N* of the EW fund portfolio leads to a 0.31% increase in next month's industry-neutral size-factor return.

5.3 Forecast size-factor return with lagged mutual fund size beta

Besides the fund-position estimates *SMB_pos* in section 5.1, we also use mutual fund's lagged size-factor beta as the forecasting variable for the size factor return. First, we use each fund's daily net return series to regress on daily Fama-French three factors and store each fund's size beta (*SMB_beta*), respectively in each month during Jan 2003 to Dec 2015. Then we aggregate each fund's size beta into the equal-weighted (EW) and value-weighted (VW) fund portfolios' size beta. The *SMB_beta* series has a strong correlation of 88.5% with the *SMB_pos* series, confirming the robustness of our estimation.

We show in Table 15.A that the lagged mutual fund size beta also positively forecasts subsequent size-factor returns. For example, for the Fama-French SMB factor, the slopes in front of the SMB-beta term in the forecasting regression is 0.029 (t=2.70) with EW fund portfolio. This forecasting power persists after we control for the $R_m - R_f$, *HML* and *MOM* factors in the forecasting month.

Our results still holds when we use industry-neutral SMB-beta to forecast industry-neutral size factor returns. We use each fund's daily net return series to regress on daily industry-neutral Fama-French three factors *(HML_FF_N* and *SMB_FF_N*) and store each fund's industry-neutral size beta (*SMB_beta_N*), respectively in each month during Jan 2003 to Dec 2015. Then we aggregate each fund's size beta into the equal-weighted (EW) and value-weighted (VW) fund portfolios' industry-neutral size beta. For example as can be seen from Table 15.B, for the *SMB_FF_N* factor, the slopes in front of the industry-neutral SMB-beta term in the forecasting regression is 0.012 (t=2.29) with EW fund portfolio.

5.4 Time-trend of SMB loading

We adopt the same procedure for our two estimators: *SMB_pos* and *SMB_beta* at weekly frequency and calculate their 12-week moving average. We show in figures 3 that mutual funds' size-factor loading exhibits a long-term upward trend. In other words, actively managed stock funds have gradually added more small-cap stocks in our sample period. More strikingly, we observe a regime switch around December 2009, as the moving-average SMB loading changed from negative to positive. It is likely due to the introduction of the Growth Enterprise Market (GEM) around that time. GEM consists largely of young, small-cap companies. More investments into these new stocks by mutual funds would mechanically increase their small-cap holdings and consequently their SMB loadings.

6. **Robustness Checks**

6.1 Results for Chinese hybrid stock mutual funds

In Table A.1, we report the summary statistics for the 145 hybrid stock mutual funds. These hybrid stock mutual funds usually invest less in stocks on average than the stock mutual funds. In other words, they focus less on stocks and more on other investments such as bonds. In Table A.4 and A.5, we show that hybrid stock funds also possess significant size-factor-timing skill, which attributes to their significant abnormal returns against passive benchmarks. But they exhibit less significant size-factor-timing skill than the stock mutual funds.

6.2 Placebo test using passive index funds

Size-factor-timing skill should only be relevant for actively managed funds because it is a dimension of their activeness. Consistently, passive index funds should not exhibit significant size-factor timing skill. To examine this implication, we conduct the placebo test by repeating the former analysis for all the passive index stock mutual funds in the Chinese stock market from 2003 to 2015. In Table A.2, we report the summary statistics for these 698 passive index stock mutual funds. We show in Table A.6 and A.7 that passive index stock funds in aggregate do not have significant size-factor-timing skill and do not outperform the market.

6.3 Timing on other factors

In this part, we report results of regression (4) and (5) with all the commonly used risk benchmarks for the Chinese stock market: $f_{1,t+1} = MKT, f_{2,t+1} = SMB, f_{3,t+1} = HML, f_{4,t+1} = MOM$. We show in Table B that Chinese actively managed stock mutual funds in aggregate only possess significant timing skill in the size factor. All the timing terms in front of *MKT*, *HML* and *MOM* factors are neither economically nor statistically significant.

6.4 Out-of-sample analysis

In this section, we investigate the out-of-sample forecasting performance of the lagged mutual funds' estimated position in size portfolios and the lagged mutual fund size beta. Goyal and Welch (2008), among others, argue that out-of-sample tests are more relevant for investors and practitioners for assessing genuine return predictability in real time, although the in-sample predictive analysis provides more efficient parameter estimates and thus more precise return forecasts. In addition, out-of-sample tests are much less affected by the econometrics issues such as the over-fitting concern, small-sample size distortion and the Stambaugh bias than in-sample regressions (Busetti and Marcucci, 2012). Hence, we investigate the out-of-sample predictive performance of the lagged mutual funds' estimated position in industry-neutral size portfolios (*SMB_pos_N*) and the lagged mutual fund industry-neutral size beta (*SMB_beta_N*).

The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t to forecast stock returns at t + 1. Following Goyal and Welch (2008), and many others, we run the out-of-sample predictive regressions recursively on each lagged estimated fund position and size beta,

$$\widehat{SMB\_N}_{t+1} = \widehat{\alpha_{mf}}_t + \widehat{P_{mf}}_t SMB\_pos\_N_{1:t;t}$$

(17)

$$\widehat{SMB\_N}_{t+1} = \widehat{\alpha_{mf}}_t + \widehat{b_{mf}}_t SMB\_beta\_N_{1:t;t}$$

(18)

where $\widehat{\alpha_{mf}}_t$ and $\widehat{P_{mf}}_t$ ($\widehat{b_{mf}}_t$) are the OLS estimates from regressing $\{SMB\_N_{s+1}\}_{s=1}^{t-1}$ on a constant and a recursively estimated measure $\{SMB\_pos\_N_{1:t;s}\}_{s=1}^{t-1}$ ($\{SMB\_beta\_N_{1:t;s}\}_{s=1}^{t-1}$). Let p be a fixed number chosen for the initial sample training, so that the future expected size-factor return can be estimated at time $t = p+1, p+2 \ldots T$. Hence, there are q (=*T*-*p*) out-of-sample evaluation periods. That is, we have q out-of-sample forecasts: $\{\widehat{SMB\_N}_{t+1}\}_{t=p}^{T-1}$. Specifically, we use the data over Jan 2003 to June 2008 as the initial estimation period, so that the forecast evaluation period spans over July 2008 to Dec 2015.

We evaluate the out-of-sample forecasting performance based on the widely used Campbell and Thompson (2008) R_{OS}^2 statistic. The R_{OS}^2 statistic measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average benchmark,

$$R_{OS}^2 = 1 - \frac{\sum_{t=p}^{T-1}(SMB\_N_{t+1} - \widehat{SMB\_N}_{t+1})^2}{\sum_{t=p}^{T-1}(SMB\_N_{t+1} - \overline{SMB\_N_{t+1}})^2}$$

(19)

where $\overline{SMB\_N_{t+1}}$ denotes the historical average benchmark corresponding to the constant expected return model,

$$\overline{SMB\_N_{t+1}} = \frac{1}{t}\sum_{s=1}^{t} SMB\_N_s.$$

(20)

Goyal and Welch (2008) show that the historical average is a very stringent out-of-sample benchmark, and individual economic variables typically fail to outperform the historical average. The R_{OS}^2 statistic lies in the range of $(-\infty, 1]$. If $R_{OS}^2 > 0$, then the forecast $\widehat{SMB\_N}_{t+1}$ outperforms $\overline{SMB\_N_{t+1}}$ in terms of MSFE.

As can be seen from Table C, all the R_{OS}^2 are significantly positive when using the lagged fund estimated position in industry-neutral size portfolios (*SMB_pos_N*) and the lagged industry-neutral size beta (*SMB_beta_N*) to forecast industry-neutral size factor returns. For example, R_{OS}^2 reaches 5.21% when using value weight *SMB_pos_N* meaure to estimate *SMB_FF_N* factor returns.

In summary, this section shows that both lagged fund estimated position in size portfolios and lagged size beta display strong out-of-sample forecasting power for the size-factor returns. In unreported results, we do the similar analysis for the general size-factor returns and find similar results.

7. Conclusion

We investigate the power of factor loading and factor timing by studying the size-factor-timing skill of Chinese mutual funds. First, we find strong evidence of significant size-factor-timing skill of Chinese mutual funds both in aggregate and cross-sectionally. We show that Chinese mutual funds' size-factor-timing skill is derived from valuable private information beyond past returns. Moreover, we show that the size-factor-timing skill arises from intra-period trading. Those funds with bigger return gap in the past show higher size-factor-timing skill in the future, and thus perform better.

Second, we find that fund performance is predictable by past fund alpha, but only within those funds that have significant size-factor-timing skill. We also find that size-factor-timing skill is persistent among high-alpha funds. But size-factor-timing skill of low-alpha funds has more random element.

Third, we track the asset-allocation style of Chinese mutual funds and forecast factor returns using a fund-position proxy. We show that in aggregate, mutual funds' lagged position dispersion in small-cap and large-cap stocks significantly forecasts size-factor returns.

Our paper emphasizes the importance of factor-timing (smart beta) in the setting of a less efficient financial market. We conclude that factor loading is not the whole picture, if investors are poor at factor timing, they can still lose to the market. On the other hand, successful factor timing does not necessarily require positive factor loading, as long as there exist less sophisticated counterparties committing systematic timing errors. We conclude that mutual funds serve as smart money in the Chinese stock market. Our forecasting results suggest that institutional trading contains valuable information to determine future asset prices.

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Figure 1: Monthly SMB FF Return (%)

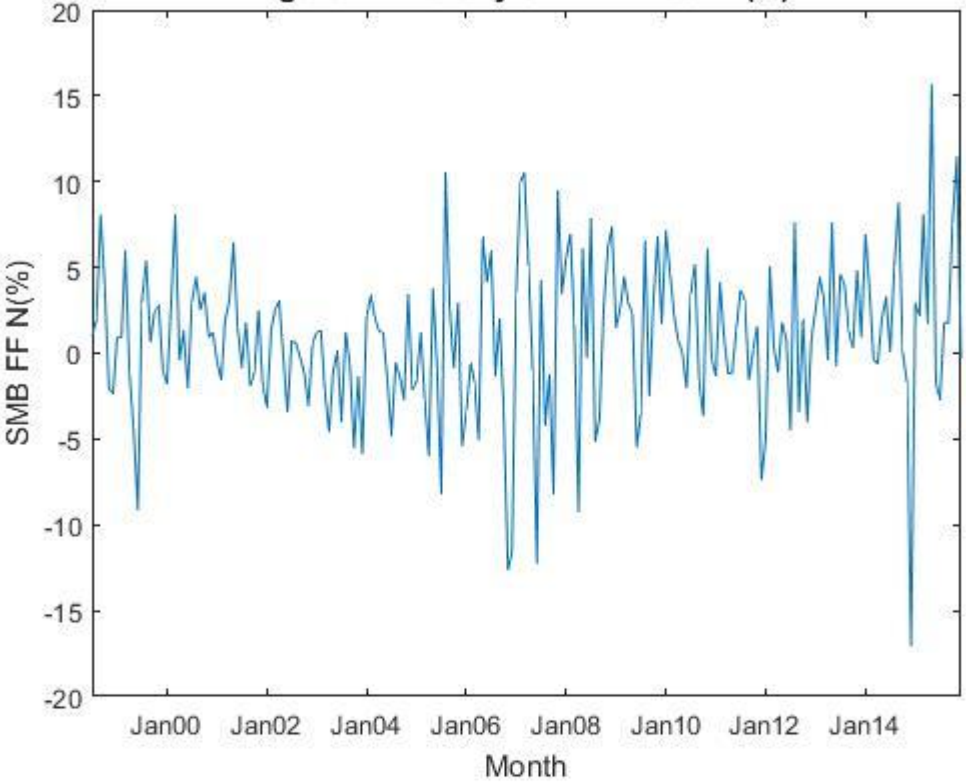

Figure 2: Monthly SMB FF Industry Neutral Return (%)

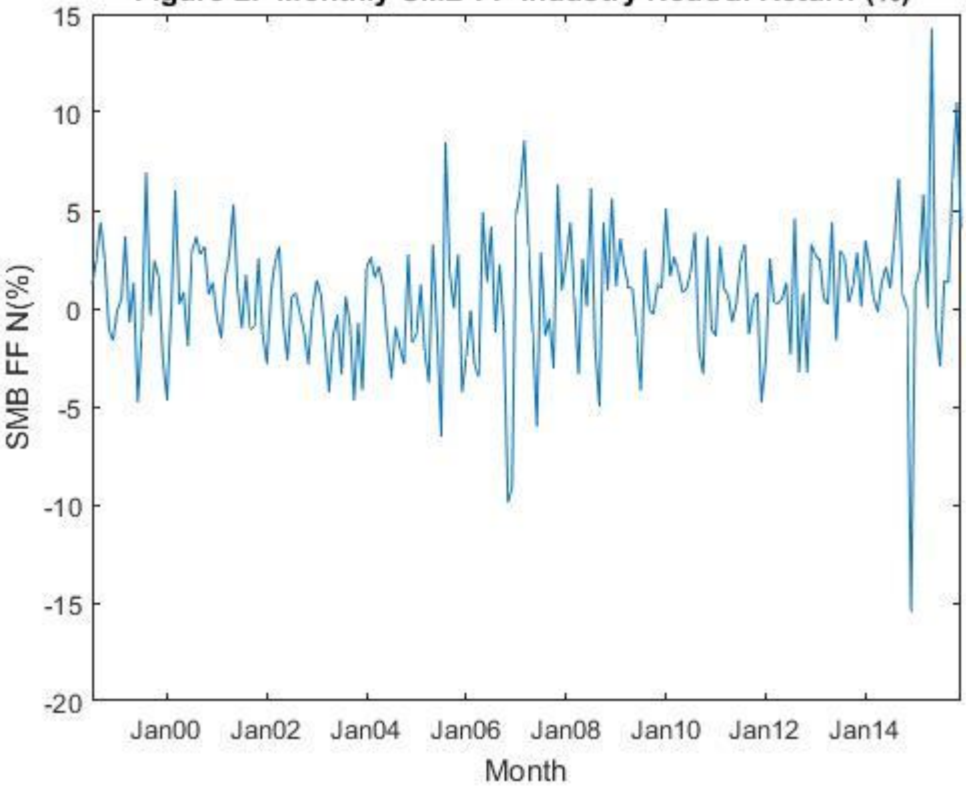

Figure 3: Time-varying Size Beta and Size Position for Chinese Mutual Funds

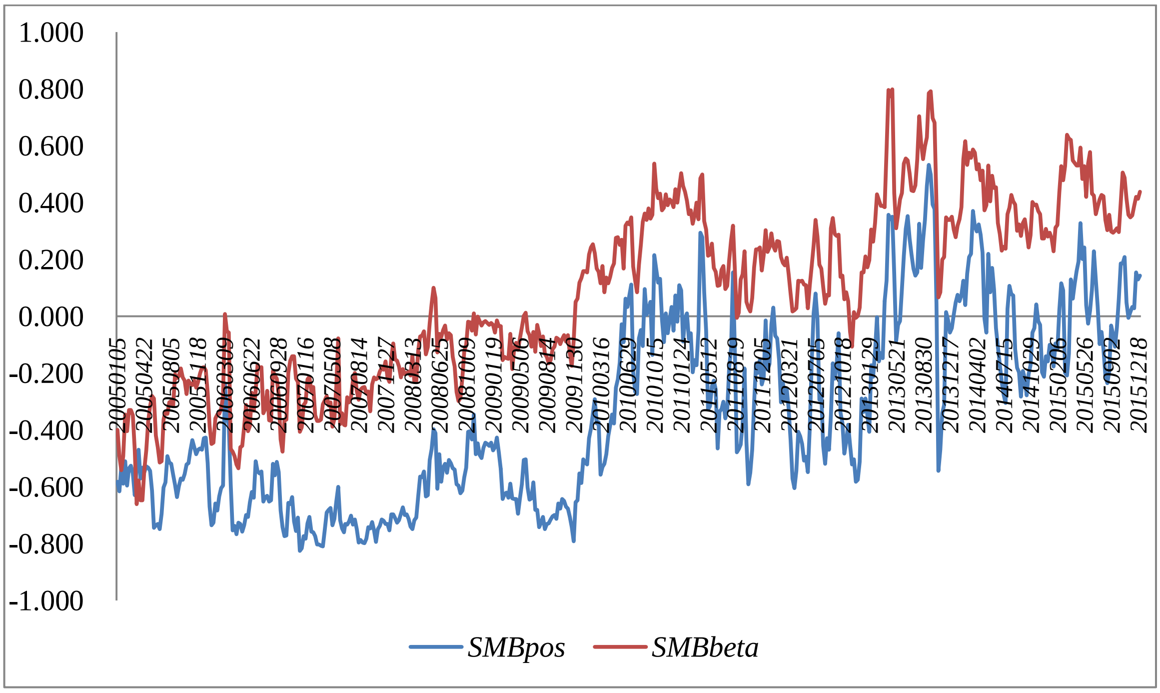

Table 1
Monthly Benchmark Factor Returns in the Chinese Stock Market

This table reports the average monthly returns, the standard deviation and t-statistics of the factors in the Chinese stock market. The whole sample period is Jan 1999 to Dec 2015, and the subsample period used to evaluate mutual fund performance is Jan 2003 to Dec 2015.

For the market risk premium $R_m - R_f$, R_m is taken as the value-weighted one-month return on stocks publicly listed on the Shenzhen A and Shanghai A stock exchanges, which represent all eligible stocks for Chinese stock mutual funds. Weights are monthly market-cap values. R_f is the risk free return, proxied by the 3-month Chinese household savings deposit rate. Since this rate is reported as an annual rate, we divide it by 12 to get a monthly R_f. Finally, the excess market return factor was constructed as the market return R_m less the risk free rate R_f.

To compute SMB_FF and HML_FF, we follow the same procedure as done in Ken French's website. We construct momentum (MOM) and reversal (REV) factors by forming six portfolios monthly, using monthly market-cap to construct small and big portfolios. For the momentum factor, we calculate the total return from 12 months prior to 2 months prior for each stock. We form monthly momentum portfolios based on this measure, with the bottom 30th percentile of stocks classified as "low", and the top 30th percentile classified as "high". For the reversal factor, we compute the return of the last month less the last trading day for each stock. We form monthly reversal portfolios based on this measure, with the bottom 30th percentile of stocks classified as "low", and the top 30th percentile of stocks classified as "high". Then we form six portfolios by intersecting the momentum and reversal portfolios with the size portfolios. The monthly momentum factor MOM=1/2 *(return on Big/High+return on Small/High)–1/2 *(return on Big/Low+return on Small/Low). The monthly reversal factor REV=1/2 *(return on Big/Low+return on Small/Low)–1/2 *(return on Big/High+return on Small/High).

For robustness checks, we also construct monthly size portfolios with different cutoffs. For example, SMB_20 defines stocks with market-cap in the top 20th percentile as "big", and stocks with market-cap in the bottom 20th percentile as "small".

1999.01-2015.12	Average Return(%)	Standard Deviation (%)	t-stat
Rm-Rf	1.00	8.49	(1.68)
SMB_FF	0.84	4.47	(2.70)
HML_FF	0.54	3.67	(2.12)
MOM	-0.17	3.81	(-0.64)
REV	0.99	3.53	(3.98)
SMB_20	1.75	7.86	(3.18)
SMB_30	1.51	6.91	(3.13)
SMB_50	1.07	5.60	(2.73)
2003.01-2015.12	Average Return(%)	Standard Deviation (%)	t-stat
Rm-Rf	1.37	8.61	(1.98)
SMB_FF	0.87	4.83	(2.24)
HML_FF	0.55	3.88	(1.78)
MOM	-0.20	4.09	(-0.62)
REV	1.14	3.80	(3.74)
SMB_20	1.82	8.50	(2.67)
SMB_30	1.58	7.45	(2.66)
SMB_50	1.14	6.11	(2.34)

Table 2
Summary Statistics for the Characteristics of the Chinese Actively Managed Stock Mutual Funds

Table 2.A reports summary statistics for our 535 sample funds during the period of 2003 to 2015. At the end of each year, we calculate the cross-sectional mean, median, standard deviation, and the interquartile range of the following fund characteristics: total net asset value, fund age, expense ratio (custodian fee plus management fee), turnover, the percentage of institutional investors in the fund holding structure, average monthly raw return and the corresponding standard deviation. The time-series averages of these variables are reported. TNA is reported in RMB billion.
In table 2.B, column 1 records the annual reporting period. Column 2 to 5 report the number of funds, the total AUM of funds, the aggregate stock market capitalization, and the ratio between the two. AUM and MktCap are in RMB billion. Ratios are in %.

Table 2.A

	Mean	Std	25^{th}	Median	75^{th}
TNA (billion)	2.28	2.86	0.47	1.24	2.88
Expense ratio (%)	1.74	0.07	1.75	1.75	1.75
Age (years)	2.59	1.77	1.09	2.50	3.75
Turnover (%)	500	340	280	406	629
Institution pct (%)	25.04	20.43	8.17	20.10	38.54
Average return (%)	1.73	1.28	1.10	1.62	2.22
Volatility (%)	8.62	2.86	7.18	8.26	9.46

Table 2.B

Report period	# of Funds	AUM of Funds (bn)	Aggr.Stock Mktcap (bn)	AUM/MktCap
4Q/2003	44	63	1245	5.06%
4Q/2004	47	66	1116	5.91%
4Q/2005	68	88	1020	8.63%
4Q/2006	105	377	2413	15.62%
4Q/2007	125	1515	9154	16.55%
4Q/2008	157	636	4540	14.01%
4Q/2009	202	1049	15080	6.96%
4Q/2010	254	989	19235	5.14%
4Q/2011	307	747	16520	4.52%
4Q/2012	354	739	18223	4.06%
4Q/2013	380	758	20042	3.78%
4Q/2014	405	716	31562	2.27%
4Q/2015	496	823	41793	1.97%

Table 3

Performance Evaluation of Chinese Actively Managed Stock Mutual Funds

Table 3.A shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the CAPM, FF3F and FF3F+MOM versions of regression (7) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0.The data cover 535 funds from Jan 2003 to Dec 2015.

Table 3.B and Table 3.C show the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (8) (HM) and regression (9) (TM) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0.The data cover 535 funds from Jan 2003 to Dec 2015.

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_t$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma I(SMB_t > 0)SMB_t + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_t$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma SMB_t SMB_t + s_{mf}SMB_t + h_{mf}HML_t + m_{mf}MOM_t + \varepsilon_t$$

Table 3.A

	12*Alpha	Rm-Rf	SMB	HML	MOM	R-square
EW						
CAPM	6.74	0.76				84%
	(2.31)	(-11.81)				
FF3F	11.15	0.82	-0.16	-0.58		92%
	(5.41)	(-12.88)	(-4.40)	(-12.91)		
FF3F+MOM	10.47	0.83	-0.11	-0.44	0.24	94%
	(5.57)	(-13.66)	(-3.43)	(-9.38)	(5.57)	
VW						
CAPM	5.16	0.77				84%
	(1.75)	(-11.39)				
FF3F	9.91	0.84	-0.18	-0.59		93%
	(4.89)	(-12.82)	(-5.33)	(-13.4)		
FF3F+MOM	9.28	0.84	-0.15	-0.46	0.22	94%
	(4.97)	(-13.40)	(-4.44)	(-9.90)	(5.21)	

Table 3.B

	EW		VW	
	HM_FF3	HM_FF3+MOM	HM_FF3	HM_FF3+MOM
12*Alpha	4.56	3.62	4.93	3.09
	(1.58)	(1.28)	(1.60)	(1.10)
Rm-Rf	0.81	0.81	0.83	0.83
	(-9.39)	(-10.40)	(-8.74)	(-9.54)
SMB	-0.28	-0.27	-0.30	-0.28
	(-4.38)	(-4.61)	(-4.70)	(-4.91)
I(SMB>0)*SMB	0.25	0.31	0.22	0.27
	(2.74)	(3.19)	(2.12)	(2.87)
HML	-0.57	-0.42	-0.58	-0.45
	(-12.77)	(-9.12)	(-13.25)	(-9.62)
MOM		0.25		0.24
		(6.03)		(5.60)
R-square	93%	94%	93%	94%

Table 3.C

	EW		VW	
	TM_FF3	TM_FF3+MOM	TM_FF3	TM_FF3+MOM
12*Alpha	6.40	5.36	6.20	4.52
	(3.60)	(3.07)	(3.22)	(2.66)
Rm-Rf	0.81	0.81	0.83	0.83
	(-9.19)	(-11.45)	(-7.54)	(-10.56)
SMB	-0.15	-0.1	-0.18	-0.14
	(-4.34)	(-4.61)	(-5.28)	(-4.27)
SMB*SMB	0.94	1.36	0.85	1.25
	(2.35)	(3.19)	(2.56)	(3.47)
HML	-0.57	-0.41	-0.58	-0.44
	(-12.86)	(-9.12)	(-13.34)	(-9.54)
MOM		0.27		0.25
		(6.03)		(5.96)
R-square	93%	94%	93%	94%

Table 4
Cross-sectional Size-Factor-Timing Performance: Bootstrap Simulation

These two tables present the results of the bootstrap analysis of size-factor-timing. For each fund with at least 12 monthly returns, we estimate the FF3F version of regression (8) and (9) model where γ measures the size-factor-timing ability. The table shows the value of $t(\gamma)$ at selected percentiles of the distribution of $t(\gamma)$ for actual stock fund returns. The table also shows the 5,000 simulation runs that produce lower values of $t(\gamma)$ at the selected percentiles than those observed for actual fund returns (%<Act) and the empirical p-values. Sim is the average of $t(\gamma)$ at the selected percentiles from the simulation. The data cover 444 funds from Jan 2003 to Dec 2015.

Table 4.A: HM+FF3F

Pct (%)	Sim	Act	%<Act	P-value
1	-2.18	-3.07	0.06	1.00
2	-1.83	-2.38	0.10	1.00
3	-1.65	-2.12	0.04	1.00
4	-1.52	-1.60	17.96	0.82
5	-1.42	-1.39	65.60	0.34
10	-1.09	-0.79	99.45	0.01
20	-0.70	-0.07	99.87	0.00
30	-0.40	0.42	100.00	0.00
40	-0.14	0.77	100.00	0.00
50	0.11	1.13	100.00	0.00
60	0.35	1.56	100.00	0.00
70	0.61	1.98	100.00	0.00
80	0.91	2.50	100.00	0.00
90	1.32	3.20	100.00	0.00
95	1.68	3.68	100.00	0.00
96	1.78	3.81	100.00	0.00
97	1.91	3.85	100.00	0.00
98	2.10	4.02	100.00	0.00
99	2.40	4.61	100.00	0.00

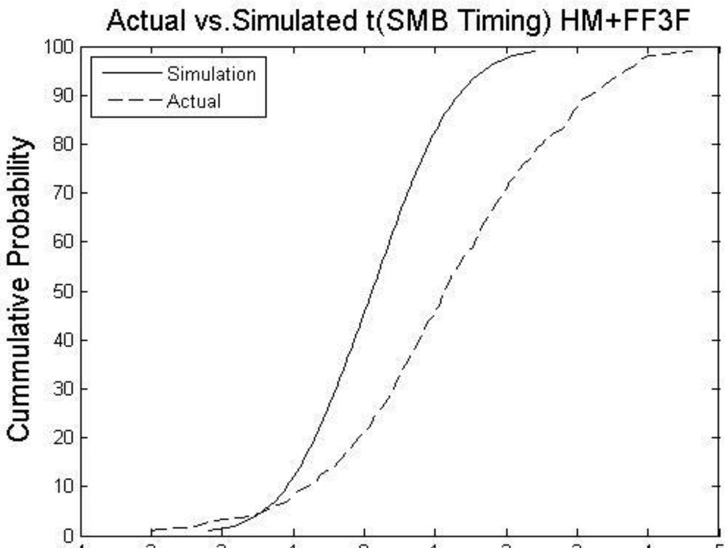

Table 4.B: TM+FF3F

Pct (%)	Sim	Act	%<Act	P-value
1	-1.98	-3.33	0.00	1.00
2	-1.68	-2.41	0.00	1.00
3	-1.51	-1.85	0.18	1.00
4	-1.39	-1.49	12.16	0.88
5	-1.30	-1.29	49.72	0.50
10	-0.99	-0.62	99.62	0.00
20	-0.62	0.11	100.00	0.00
30	-0.34	0.51	100.00	0.00
40	-0.09	1.08	100.00	0.00
50	0.15	1.49	100.00	0.00
60	0.39	1.92	100.00	0.00
70	0.65	2.44	100.00	0.00
80	0.96	3.17	100.00	0.00
90	1.39	4.02	100.00	0.00
95	1.76	4.77	100.00	0.00
96	1.87	4.97	100.00	0.00
97	2.01	5.18	100.00	0.00
98	2.20	5.38	100.00	0.00
99	2.51	5.63	100.00	0.00

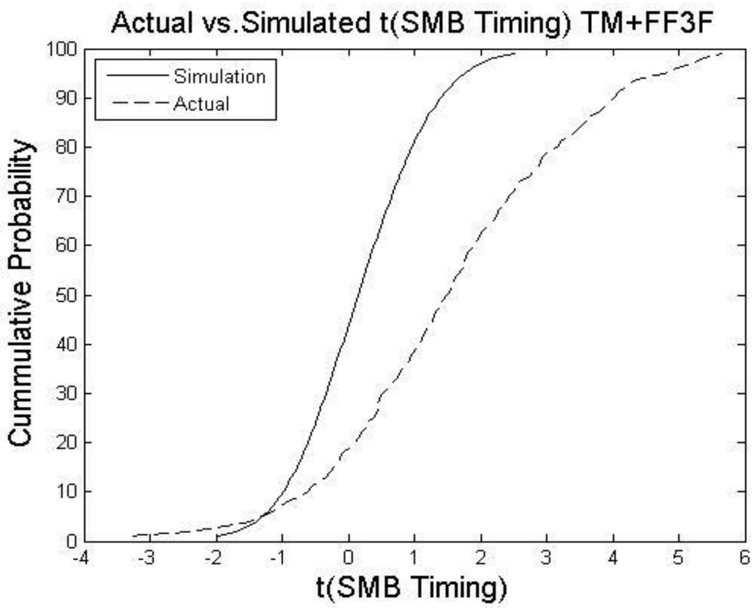

Table 5
Test for Cross-sectional Relationship between Fund Characteristics and Size-Factor-Timing Skill

Table 5 reports the results of cross-sectional regressions that analyze the effects of fund characteristics on size-factor-timing skill. The dependent variable is the t-statistics of the size-factor-timing coefficient: $t(\gamma)$ of each fund estimated with the FF3F and FF3F+MOM version of regression (2) (HM) and (3) (TM) in the time periods of Jan 2003 to Dec 2015. The main explanatory variables include fund age (log) in years, time series average of the TNA (log) in RMB billion, expense ratio (%), percentage of institutional investors in the fund holding structure (%), turnover and close end fund dummy correspondingly for each fund. The slopes and t-statistics (in parentheses) of the explanatory variables are reported in the table. The data cover 444 funds with at least 12 monthly returns from Jan 2003 to Dec 2015.

$$t\,(\gamma)_i = \alpha_i + \beta_1 log(TNA)_i + \beta_2 log(Age)_i + \beta_3 Exp_i + \beta_4 Ins\ pct_i + \beta_5 Turnover_i + \beta_6 Close\ end_i + \varepsilon_i$$

	HM_FF3F	HM_FF3F+MOM	TM_FF3F	TM_FF3F+MOM
Intercept	2.86	1.60	2.80	0.93
	(1.27)	(0.73)	(1.07)	(0.36)
log(TNA)	-0.18	-0.14	-0.20	-0.14
	(-2.55)	(-2.06)	(-2.39)	(-1.96)
log(Age)	0.64	0.83	0.73	1.01
	(4.36)	(5.88)	(4.30)	(6.10)
Expense ratio	-0.49	-0.72	-0.27	-0.52
	(-0.46)	(-0.70)	(-0.22)	(-0.43)
Institution pct	0.01	0.01	0.01	0.01
	(0.50)	(0.54)	(0.23)	(0.33)
Turnover	0.07	0.05	0.08	0.06
	(1.80)	(1.99)	(1.97)	(1.95)
Close end dummy	-0.24	-0.38	-0.68	-1.07
	(-0.70)	(-1.21)	(-1.39)	(-2.94)
Adj R-square	8%	7%	6%	8%

Table 6
Size Factor Timing VS. Size Factor Reaction

Table 6.A reports the results of AR (1) regression of different size factors: SMB_FF, SMB_20, SMB_30 and SMB_50 in the first three rows. The fourth row reports the p-values of the ADF test for these size factors. Table 6.B reports the results of FF3F and FF3F+MOM versions of regression estimated on the equal-weighted (EW) net returns on the portfolios of actively managed stock mutual funds, which help to distinguish size-factor-timing from size-factor reaction. The monthly intercepts of alpha (in percentage %), the slopes of the factors and t-statistics (in parentheses) are reported in the table. The data cover 535 funds from Jan 2003 to Dec 2015.

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma \varepsilon_t SMB_t + \beta SMB_{t-1} SMB_t + s_{mf} SMB_t + HML_t + m_{mf} MOM_t + \varepsilon_t,$$

$$R_{mf,t} - R_{ft} = \alpha_{mf} + b_{mf}(Rm_t - Rf_t) + \gamma I(\varepsilon_t > 0) SMB_t + \beta I(SMB_{t-1} > 0) SMB_t + s_{mf} SMB_t + h_{mf} HML_t + m_{mf} MOM_t + \varepsilon_t$$

Table 6.A

	SMB_FF(t)	SMB_20(t)	SMB_30(t)	SMB_50(t)
Intercept	0.01	0.02	0.01	0.01
	(1.95)	(2.35)	(2.32)	(2.07)
SMB(t-1)	0.11	0.10	0.10	0.09
	(1.32)	(1.18)	(1.27)	(1.07)
R-square	0.01	0.01	0.01	0.01
ADF P-value	0.001	0.001	0.001	0.001

Table 6.B

	TM_FF3F	TM_FF3+MOM	HM_FF3	HM_FF3F+MOM
Alpha(t)	0.59	0.52	0.40	0.33
	(3.50)	(2.98)	(1.58)	(1.39)
Rm-Rf(t)	0.81	0.81	0.81	0.81
	(-9.15)	(-10.28)	(-9.59)	(-10.36)
SMB(t)	-0.14	-0.09	-0.29	-0.28
	(-3.95)	(-2.76)	(-4.46)	(-4.69)
ε(t)*SMB(t)	0.92	1.42		
	(2.22)	(3.78)		
I(ε(t)>0)*SMB(t)			0.20	0.26
			(1.95)	(2.55)
SMB(t-1)*SMB(t)	0.24	-0.17		
	(0.35)	(-0.29)		
I(SMB(t-1)>0)*SMB(t)			0.08	0.07
			(1.11)	(1.05)
HML(t)	-0.57	-0.41	-0.56	-0.42
	(-12.67)	(-8.99)	(-12.42)	(-8.92)
MOM(t)		0.27		0.25
		(6.38)		(5.96)
R-square	93%	94%	93%	94%

Table 7
Aggregate Performance Evaluation of "All Holdings" Portfolio

The “All Holdings” portfolio is formed as follows: at the end of each semiannual reporting period, the portfolio is rebalanced to mimic the exact aggregate holdings of the stock mutual funds in my sample. It is then held for the next six month before the next rebalancing takes place. As a result, this portfolio mimics the aggregate mutual fund holdings at six-month intervals.

Table 7.A shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the CAPM, FF3F and FF3F+MOM versions of regression (7) estimated on the “All Holdings” portfolio of actively managed stock mutual funds. Table 7.B show the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (8) (HM) and regression (9) (TM) estimated on the “All Holdings” portfolios of actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0.The data cover 535 funds from July 2003 to Dec 2015.

Table 7.A

VW "All Holdings" Returns	12*Alpha	Rm-Rf	SMB	HML	MOM	R-square
CAPM	3.10	0.95				0.91
	(1.22)	(-2.29)				
FF3F	8.05	1.00	-0.26	-0.45		0.96
	(4.58)	(0.16)	(-8.71)	(-12.02)		
FF3F+MOM	7.43	1.00	-0.22	-0.34	0.22	0.97
	(4.71)	(0.41)	(-8.09)	(-8.48)	(6.10)	

Table 7.B

VW "All Holdings" Returns	HM_FF3	HM_FF3+MOM	TM_FF3	TM_FF3+MOM
12*Alpha	7.61	5.86	8.41	6.74
	(2.80)	(2.40)	(4.14)	(3.67)
Rm-Rf	1.00	1.00	1.00	1.00
	(0.10)	(0.19)	(0.23)	(0.23)
SMB	-0.27	-0.26	-0.26	-0.22
	(-4.87)	(-5.17)	(-8.70)	(-7.97)
I(SMB>0)*SMB/SMB^2	0.02	0.07	-0.12	0.23
	(0.22)	(0.84)	(-0.35)	(0.74)
HML	-0.49	-0.33	-0.46	-0.33
	(-11.89)	(-8.26)	(-11.97)	(-8.22)
MOM		0.22		0.23
		(6.15)		(6.12)
R-square	0.96	0.97	0.96	0.97

Table 8

Size-Factor-Timing Skill of Fund Portfolios Sorted by Past Return Gap

Table 8 reports the size-factor-timing coefficient: γ and its t-statistic: $t(\gamma)$ for the five fund portfolios. At each month-end, we sort mutual funds into quintile portfolios based on their past 12 months' return gap and hold each portfolio for one month. We require funds to have the past 12 months' return gap data to be included in our sorting procedure. We then report the size-factor-timing coefficient: γ and its t-statistic $t(\gamma)$ estimated with the FF3F version of regression (2) (HM) and (3) (TM) of each equal weighted mutual fund portfolio in the time periods of July 2003 to Dec 2015. The data cover 444 funds with at least 12 monthly returns from July 2003 to Dec 2015.

Table 8

Past Return Gap	γ: HM_FF3	γ: HM_FF3+MOM	γ: TM_FF3	γ: TM_FF3+MOM
1-Low	0.14	0.17	0.43	0.65
	(1.16)	(1.40)	(0.99)	(1.43)
2	0.20	0.22	0.88	0.97
	(1.87)	(1.93)	(1.86)	(2.17)
3	0.23	0.29	1.02	1.31
	(2.23)	(2.62)	(2.32)	(2.80)
4	0.25	0.33	1.05	1.49
	(2.60)	(2.95)	(2.67)	(3.61)
5-High	0.33	0.37	1.41	1.66
	(2.95)	(3.10)	(3.21)	(4.29)

Table 9
Test for Cross-sectional Relationship between Fund Return Gap and Size-Factor-Timing Skill

Table 9 reports the results of the whole sample cross-sectional regressions that analyze the effects of fund return gap on size-factor-timing skill. The dependent variable is the t-statistics of the size-factor-timing coefficient: $t(\gamma)$ of each fund estimated with the FF3F and FF3F+MOM version of regression (2) (HM) and (3) (TM) in the time periods of July 2003 to Dec 2015. The main explanatory variables include whole sample average of monthly return gap, fund age (log) in years, time series average of the TNA (log) in RMB billion and turnover correspondingly for each fund. The slopes and t-statistics (in parentheses) of the explanatory variables are reported in the table. The data cover 444 funds with at least 12 monthly returns from July 2003 to Dec 2015.

$$t\ (\gamma)_i = \alpha_i + \beta_1 Return\ Gap_i + \varepsilon_i$$

$$t\ (\gamma)_i = \alpha_i + \beta_1 Return\ Gap_i + \beta_2 log(TNA)_i + \beta_3 log(Age)_i + \beta_4 Turnover_i + \varepsilon_i$$

Table 9

	t(γ): HM_FF3F		t(γ): TM_FF3F	
Intercept	1.05	2.38	1.36	2.66
	(4.79)	(1.70)	(5.35)	(1.61)
Return gap	0.62	0.59	0.72	0.69
	(6.03)	(5.80)	(6.78)	(5.78)
log(TNA)		-0.17		-0.18
		(-2.76)		(-2.39)
log(age)		0.55		0.57
		(4.26)		(3.71)
Turnover		0.05		0.06
		(1.62)		(1.87)
Adj r-square	7.61%	15.84%	7.63%	14.50%

Table 10
Size-Factor Timing of U.S. Actively Managed Stock Mutual Funds

Table 10.A shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the CAPM, FF3F and FF3F+MOM versions of regression (7) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of U.S. actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0.The data cover 3496 funds from Jan 1980 to Dec 2014.

Table 10.B and Table 10.C show the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (8) (HM) and regression (9) (TM) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of U.S. actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0.The data covers 3496 funds from Jan 1980 to Dec 2014.

Table 10.D present the results of the bootstrap analysis of cross sectional size-factor-timing. For each fund with at least 12 monthly returns, we estimate the FF3F version of regression (8) HM timing model where γ measures the size-factor-timing ability. The table shows the value of $t(\gamma)$ at selected percentiles of the distribution of $t(\gamma)$ for actual stock fund returns. The table also shows the 5,000 simulation runs that produce lower values of $t(\gamma)$ at the selected percentiles than those observed for actual fund returns (%<Act) and the empirical p-values. Sim is the average of $t(\gamma)$ at the selected percentiles from the simulation. The data covers 3496 funds from Jan 1980 to Dec 2014.

Table 10.A

	12*Alpha	Rm-Rf	SMB	HML	MOM	R-square
EW						
CAPM	-0.20	0.92				0.97
	(-0.49)	(-10.17)				
FF3F	-0.40	0.91	0.16	0.03		0.99
	(-1.28)	(-15.55)	(17.45)	(3.13)		
FF3F+MOM	-0.45	0.91	0.15	0.03	0.01	0.99
	(-1.43)	(-15.07)	(17.40)	(3.26)	(0.94)	
VW						
CAPM	-0.54	0.92				0.99
	(-1.84)	(-15.09)				
FF3F	-0.63	0.91	0.06	0.01		0.99
	(-2.25)	(-16.05)	(7.24)	(1.64)		
FF3F+MOM	-0.60	0.91	0.06	0.01	0.00	0.94
	(-2.10)	(-15.85)	(7.25)	(1.48)	(0.57)	

Table 10.B

	EW		VW	
	HM_FF3	HM_FF3+MOM	HM_FF3	HM_FF3+MOM
12*Alpha	-0.62	-0.69	-0.70	-0.67
	(-1.37)	(-1.51)	(-1.74)	(-1.63)
Rm-Rf	0.91	0.91	0.91	0.91
	(-15.39)	(-14.90)	(-15.92)	(-15.71)
SMB	0.15	0.15	0.05	0.06
	(8.94)	(8.86)	(3.72)	(3.75)
I(SMB>0)*SMB	0.02	0.02	0.01	0.01
	(0.67)	(0.71)	(0.26)	(0.23)
HML	0.03	0.03	0.01	0.01
	(3.18)	(3.31)	(1.66)	(1.50)
MOM		0.01		0.003
		(0.97)		(0.56)
R-square	0.99	0.99	0.99	0.99

Table 10.C

	EW		VW	
	TM_FF3	TM_FF3+MOM	TM_FF3	TM_FF3+MOM
12*Alpha	-0.52	-0.90	-0.74	-0.71
	(-1.57)	(-2.38)	(-2.49)	(-2.36)
Rm-Rf	0.91	0.91	0.91	0.91
	(-15.37)	(-14.57)	(-15.87)	(-15.70)
SMB	0.15	0.15	0.06	0.06
	(16.76)	(16.74)	(6.81)	(6.81)
SMB*SMB	0.10	0.09	0.09	0.09
	(1.12)	(1.06)	(1.14)	(1.18)
HML	0.03	0.03	0.02	0.01
	(3.25)	(3.36)	(1.77)	(1.60)
MOM		0.01		0.003
		(0.87)		(0.65)
R-square	0.99	0.99	0.99	0.99

Table 10.D

Pct (%)	Sim	Act	%<Act	P-value
1	-2.55	-2.74	1.00%	0.99
2	-2.25	-2.36	3.00%	0.97
3	-2.06	-2.21	0.00%	1.00
4	-1.92	-2.03	2.00%	0.98
5	-1.81	-1.94	0.00%	1.00
10	-1.43	-1.50	2.00%	0.98
20	-0.78	-1.00	20.00%	0.80
30	-0.61	-0.62	63.00%	0.37
40	-0.33	-0.31	70.00%	0.31
50	-0.01	0.07	100.00%	0.00
60	0.15	0.29	100.00%	0.00
70	0.43	0.60	100.00%	0.00
80	0.75	0.97	100.00%	0.00
90	1.21	1.51	100.00%	0.00
95	1.59	2.02	100.00%	0.00
96	1.70	2.18	100.00%	0.00
97	1.84	2.41	100.00%	0.00
98	2.03	2.62	100.00%	0.00
99	2.32	3.04	100.00%	0.00

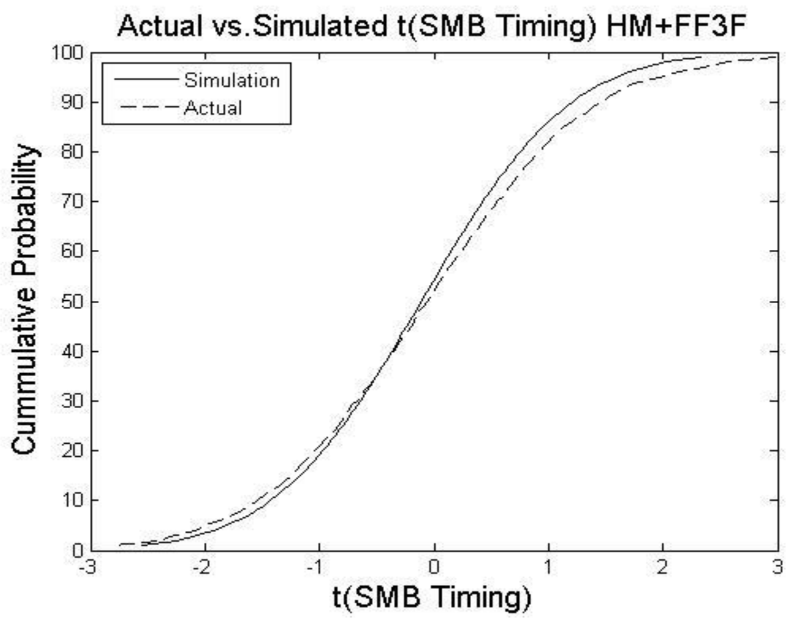

Table 11
Performance of Funds Sorted by Past Alpha or by Past Size-Factor-Timing Skill

Table 11.A reports the monthly after expense CAPM, FF3F and FF3F+MOM alpha, in percentage points. At each month-end, we sort mutual funds into quintile portfolios based on their past 12-month CAPM (FF3F and FF3F+MOM) alpha correspondingly and hold each portfolio for one month. We then report the CAPM (FF3F and FF3F+MOM) alpha and their t-statistics of each portfolio. The data covers 444 funds with at least 12 monthly returns from Jan 2003 to Dec 2015.

Table 11.B reports the monthly after expense CAPM, FF3F and FF3F+MOM alpha, in percentage points. At each month-end, we sort mutual funds into quintile portfolios based on their t-statistics of the size-factor-timing coefficient: $t(\gamma)$ estimated with the FF3F version of regression (8) (HM) using their past 12-month raw returns. We then report the CAPM (FF3F and FF3F+MOM) alpha and their t-statistics of each portfolio. The data cover 444 funds with at least 12 monthly returns from Jan 2003 to Dec 2015.

Table 11.A

	1-Low	2	3	4	5-High	High-Low
CAPM_Alpha	0.31	0.51	0.53	0.62	0.81	0.50
	(1.61)	(2.22)	(2.14)	(2.30)	(2.57)	(2.75)
FF3F_Alpha	0.75	0.79	0.91	1.03	1.21	0.46
	(4.27)	(4.35)	(5.04)	(5.46)	(5.78)	(4.00)
FF3F+MOM_Alpha	0.72	0.80	0.84	0.90	1.09	0.37
	(4.03)	(4.70)	(4.98)	(5.34)	(5.71)	(3.09)

Table 11.B

	1-Low	2	3	4	5-High	High-Low
CAPM_Alpha	0.49	0.52	0.60	0.50	0.57	0.09
	(2.00)	(2.01)	(2.30)	(2.17)	(2.35)	(0.70)
FF3_Alpha	0.85	0.83	0.98	0.93	0.97	0.12
	(4.35)	(4.57)	(5.01)	(4.85)	(5.58)	(1.03)
FF3F+MOM_Alpha	0.79	0.77	0.91	0.87	0.89	0.10
	(4.23)	(4.78)	(4.97)	(4.49)	(5.81)	(0.83)

Table 12
Performance of Fund Portfolios Double-Sorted by Past Alpha and Size-Factor-Timing Skill

These three tables report the monthly after expense CAPM, FF3F and FF3F+MOM alpha of the fund portfolios on the monthly independent double-sorts by past alpha and size-factor-timing skill correspondingly, in percentage points. Funds with alpha (timing skill) in the top 20^{th} percentile were classified as “high”, while funds with alpha (timing skill) in the bottom 20^{th} percentile were classified as “low”. Funds with alpha (timing skill) in the middle 60 percentiles (20^{th} to 80^{th} percentile) were classified as “medium”. In table 12.A, 12.B and 12.C, past alpha are estimated using past 12-month raw returns from the CAPM, FF3F and FF3F+MOM model correspondingly. The size-factor-timing skill is measured with the t-statistic of the size-factor-timing coefficient: $t(\gamma)$ estimated with the FF3F version of regression (8) (HM) using past 12-month raw returns. The data cover 444 funds with at least 12 monthly returns from Jan 2003 to Dec 2015.

Table 12.A :CAPM	Past Size-Factor-Timing Skill			
Past CAPM_Alpha	1-Low	2	3-High	High-Low
1-Low	0.58	0.52	0.13	-0.45
	(2.40)	(2.02)	(0.46)	(-2.38)
2	0.47	0.54	0.57	0.10
	(1.92)	(2.23)	(2.13)	(0.92)
3-High	0.68	0.72	0.82	0.14
	(2.60)	(3.33)	(4.12)	(1.46)
High-Low	0.10	0.20	0.69	0.23
	(0.74)	(1.56)	(3.32)	(1.87)

Table 12.B: FF3F	Past Size-Factor-Timing Skill			
Past FF3F_Alpha	1-Low	2	3-High	High-Low
1-Low	0.85	0.77	0.47	-0.38
	(4.22)	(3.17)	(2.15)	(-2.49)
2	0.86	0.92	0.97	0.11
	(4.61)	(4.89)	(5.41)	(1.02)
3-High	0.99	1.05	1.27	0.28
	(4.92)	(4.99)	(6.47)	(1.89)
High-Low	0.14	0.28	0.8	0.42
	(0.68)	(1.73)	(4.65)	(2.07)

Table 12.C: FF3F+MOM	Past Size-Factor-Timing Skill			
Past FF3F+MOM_Alpha	1-Low	2	3-High	High-Low
1-Low	0.81	0.76	0.41	-0.40
	(3.99)	(3.66)	(1.96)	(-2.67)
2	0.89	0.86	0.98	0.09
	(4.51)	(4.93)	(5.53)	(0.86)
3-High	0.96	0.97	1.20	0.23
	(4.91)	(4.98)	(6.24)	(1.75)
High-Low	0.15	0.21	0.79	0.39
	(0.78)	(1.68)	(4.35)	(2.13)

Table 13
Forecast Size Factor Return with Estimated Actively Managed Stock Mutual Funds' Position in Small and Big Size Portfolios

These tables report the results of forecasting monthly size factor return with our estimated stock mutual funds' position in different size portfolios. First, we construct monthly formed size portfolios based on the market-cap of the stocks at the end of last month. Stocks with market-cap in the top 30^{th} percentile of all market-cap for publicly listed Chinese A stocks were classified as "big", while stocks with market-cap in the bottom 30^{th} percentile were classified as "small". Stocks with market-cap in the middle 40 percentiles (30^{th} to 70^{th} percentile) were classified as "medium". The value-weighted monthly returns for each portfolio: R_{Big}, R_{Medium} and R_{Small} were computed using monthly market-cap data. Then we solve the following optimization problem with each mutual fund's daily net return and estimate their monthly position: POS_{Big}, POS_{Medium} and POS_{Small} in different size portfolios. Finally, we aggregate each fund's positions into the equal-weighted (EW) and value-weighted (VW) positions in different size portfolios respectively (*SMB_pos=Small_pos-Big_pos*). All the results in these tables cover 444 funds with at least 12 monthly returns from Jan 2003 to Dec 2015.

$$Min \quad \left\| R_{MF,t} - R_{compond,t} \right\|_2^2 = \frac{1}{T}\sum_{t=1}^{T}\left(R_{MF,t} - R_{compond,t}\right)^2,$$

$$R_{compond,t} = POS_{Big} * R_{Big,t} + POS_{Medium} * R_{Medium,t} + POS_{Small} * R_{Small,t} \ ,$$

$$\text{s.t } \sum_{i=1}^{3} POS_i \leq 1 \quad \text{and } \ POS_i \geq 0 \ .$$

Table 13.A reports the p-values of the ADF test for the equal-weighted (EW) and value-weighted (VW) monthly estimated funds' position in different size portfolios.

Table 13.B reports the slopes of the (*SMB_pos*) position and t-statistics (in parentheses) for the forecasting regression, which we use our aggregate equal-weighted (EW) and value-weighted (VW) estimated position dispersion in small and big size portfolios (*SMB_pos*) in month t to forecast different versions of size factor return (SMB_FF, SMB_50,SMB_30 and SMB_20) in month t+1. We also report the regression results when we control $R_m - R_f$, *HML* and *MOM* factors in month t+1.

$$SMB_{t+1} = \alpha_{mf} + P_{mf}SMB\_pos_t + \varepsilon_{t+1} \ ,$$

$$SMB_{t+1} = \alpha_{mf} + P_{mf}SMB\_pos_t + b_{mf}(Rm_{t+1} - Rf_{t+1}) + h_{mf}HML_{t+1} + m_{mf}MOM_{t+1} + \varepsilon_{t+1} \ .$$

In Table 13.C, we sort the months (t) from Jan 2003 to Dec 2015 based on the aggregate equal-weighted (EW) monthly estimated position dispersion in small and big size portfolios (*SMB_pos*) into four groups. In each quartile (approximately 40 months), we report the average monthly size-factor returns and t-statistics in the next months (t+1).

In Table 13.D, we try to analyze the cross-sectional difference of forecasting power for funds with different timing skill. At each month-end, we sort mutual funds into quartile portfolios based on their t-statistics of the size-factor-timing coefficient: $t(\gamma)$ estimated with the FF3F version of regression (2) (HM) using their past 12-month raw returns. Then in each quartile portfolio, we follow the procedure in Table 9.B to get the equal-weighted (EW) estimated *SMB_pos* and run the two versions of forecasting regression. We report the slopes of the (*SMB_pos*) position and t-statistics (in parentheses).

Table 13.A

Equal-Weighted				
ADF Test	Big_pos	Medium_pos	Small_pos	SMB_pos
P-value	0.225	0.001	0.001	0.021
Value-Weighted				
ADF Test	Big_pos	Medium_pos	Small_pos	SMB_pos
P-value	0.254	0.001	0.001	0.039

Table 13.B

Equal-Weighted	SMB_FF (t+1)	SMB_50 (t+1)	SMB_30 (t+1)	SMB_20 (t+1)
SMB_pos (t)	0.028	0.035	0.046	0.063
	(2.73)	(2.72)	(2.94)	(3.09)
R-square	4.70%	5.10%	5.40%	6.00%
	Control RM-Rf (t+1), HML (t+1), MOM (t+1)			
SMB_pos (t)	0.021	0.023	0.03	0.035
	(2.05)	(1.94)	(2.12)	(2.14)
R-square	15.50%	23.50%	26.20%	27.90%
Value-Weighted	**SMB_FF (t+1)**	**SMB_50 (t+1)**	**SMB_30 (t+1)**	**SMB_20 (t+1)**
SMB_pos (t)	0.031	0.039	0.052	0.060
	(2.88)	(2.92)	(3.18)	(3.25)
R-square	5.20%	5.30%	6.30%	6.50%
	Control RM-Rf (t+1), HML (t+1), MOM (t+1)			
SMB_pos (t)	0.023	0.026	0.035	0.040
	(2.18)	(2.13)	(2.35)	(2.39)
R-square	15.80%	23.80%	26.70%	28.50%

Table 13.C

SMB_POS	SMB_FF (%)	SMB_50 (%)	SMB_30 (%)	SMB_20 (%)
1-High	2.57	3.46	4.57	5.42
	(4.16)	(3.90)	(3.94)	(4.13)
2	1.40	1.52	1.94	2.06
	(1.79)	(1.51)	(1.56)	(1.61)
3	-0.60	-0.58	-0.71	-0.63
	(-0.72)	(-0.62)	(-0.65)	(-0.54)
4-Low	-1.34	-1.35	-1.44	-1.59
	(-1.53)	(-1.47)	(-1.50)	(-1.69)
High-Low	3.91	4.81	6.01	7.01
	(3.25)	(3.30)	(3.53)	(3.63)

Table 13.D					Control RM-Rf (t+1), HML (t+1), MOM (t+1)			
	SMB_FF	SMB_50	SMB_30	SMB_20	SMB_FF	SMB_50	SMB_30	SMB_20
				1-High (>75%)				
SMB_pos	0.038	0.048	0.062	0.076	0.022	0.026	0.033	0.038
	(2.91)	(3.08)	(3.60)	(3.85)	(2.32)	(2.46)	(2.77)	(3.03)
R-square	6.30%	6.60%	7.60%	8.10%	18.50%	25.50%	28.40%	32.10%
				2 (50%-75%)				
SMB_pos	0.027	0.034	0.044	0.051	0.019	0.023	0.030	0.035
	(2.66)	(2.51)	(2.72)	(2.78)	(2.12)	(2.05)	(2.24)	(2.29)
R-square	4.40%	4.60%	5.00%	5.20%	14.10%	22.00%	24.50%	26.20%
				3 (25%-50%)				
SMB_pos	0.023	0.030	0.039	0.045	0.017	0.020	0.025	0.033
	(2.14)	(2.19)	(2.36)	(2.39)	(1.90)	(1.94)	(2.06)	(2.07)
R-square	3.20%	3.30%	4.00%	4.10%	12.90%	22.50%	25.00%	25.60%
				4-Low (<25%)				
SMB_pos	0.020	0.027	0.034	0.039	0.015	0.017	0.022	0.024
	(1.59)	(1.68)	(1.79)	(1.79)	(1.19)	(1.18)	(1.23)	(1.20)
R-square	1.90%	2.10%	2.40%	2.40%	10.90%	18.90%	21.10%	22.40%

Table 14
Forecast Industry-neutral Size Factor Return with Estimated Stock Mutual Funds' Position in Industry-neutral Size Portfolios

These tables report the results of forecasting monthly industry-neutral size factor return with our estimated stock mutual funds' position in different size portfolios.

In Table 14.A, we report the average monthly returns, the standard deviation and t-statistics of the industry-neutral factors as well as their return correlation with the non-industry-neutral counterparts in the Chinese stock market. We sort stocks by their market cap and B/M ratios within each of the 24 industries classified by the GICS, and then value weight stock returns across the industry to get the industry-neutral factor returns.

In Table 14.B, we report the slopes of the (*SMB_pos_N*) position and t-statistics (in parentheses) for the forecasting regression, which we use our aggregate equal-weighted (EW) and value-weighted (VW) estimated position dispersion in industry-neutral small and big size portfolios (*SMB_pos_N*) in month t to forecast different versions of industry-neutral size factor return (*SMB_FF_N*, *SMB_50_N*, *SMB_30_N and SMB_20_N*) in month t+1. We also report the regression results when we control $R_m - R_f$, and *HML_N* factors in month t+1.

$$SMB\_N_{t+1} = \alpha_{mf} + P_{mf} SMB\_pos\_N_t + \varepsilon_{t+1} \ ,$$

$$SMB\_N_{t+1} = \alpha_{mf} + P_{mf} SMB\_pos\_N_t + b_{mf}(Rm_{t+1} - Rf_{t+1}) + h_{mf} HML\_N_{t+1} + \varepsilon_{t+1} \ .$$

Table 14.A

2003.01-2015.12	Average Return(%)	Standard Deviation	t-stat	Corr
SMB_FF_N	0.62	3.58	(2.16)	0.94
HML_FF_N	0.61	2.59	(2.95)	0.83
SMB_20_N	1.35	6.37	(2.65)	0.97
SMB_30_N	1.22	5.21	(2.92)	0.97
SMB_50_N	0.78	4.01	(2.42)	0.96

Table 14.B

Equal-Weighted	SMB_FF_N (t+1)	SMB_50_N (t+1)	SMB_30_N (t+1)	SMB_20_N (t+1)
SMB_pos_N (t)	0.014	0.030	0.023	0.038
	(1.974)	(2.480)	(2.316)	(2.737)
R-square	2.52%	3.92%	3.43%	5.49%
	Control RM-Rf (t+1), HML_FF_N (t+1), MOM (t+1)			
SMB_pos (t)	0.012	0.026	0.020	0.027
	(1.756)	(2.190)	(2.060)	(2.705)
R-square	7.18%	9.40%	8.93%	12.28%
Value-Weighted	**SMB_FF_N (t+1)**	**SMB_50_N (t+1)**	**SMB_30_N (t+1)**	**SMB_20_N (t+1)**
SMB_pos_N (t)	0.015	0.032	0.025	0.039
	(2.116)	(2.634)	(2.475)	(2.696)
R-square	2.88%	4.39%	3.90%	4.26%
	Control RM-Rf (t+1), HML_FF_N (t+1), MOM (t+1)			
SMB_pos (t)	0.013	0.028	0.022	0.027
	(1.908)	(2.356)	(2.229)	(2.667)
R-square	7.52%	9.85%	9.36%	11.70%

Table 15
Forecast Size-Factor Return with Lagged Mutual Fund Size Beta

Table 15.A reports the slopes of the *SMB_beta* and t-statistics (in parentheses) for the forecasting regression, which we use our aggregate equal-weighted (EW) and value-weighted (VW) fund portfolio's size factor beta in month t to forecast different versions of size factor return (*SMB_FF, SMB_50,SMB_30 and SMB_20*) in month t+1. We also report the regression results when we control $R_m - R_f$, *HML* and *MOM* factors in month t+1.

$$SMB_{t+1} = \alpha_{mf} + P_{mf} SMB\_beta_t + \varepsilon_{t+1} \ ,$$

$$SMB_{t+1} = \alpha_{mf} + P_{mf} SMB\_beta_t + b_{mf}(Rm_{t+1} - Rf_{t+1}) + h_{mf} HML_{t+1} + m_{mf} MOM_{t+1} + \varepsilon_{t+1} \ .$$

Table 15.B reports the slopes of the *SMB_beta_N* and t-statistics (in parentheses) for the forecasting regression, which we use our aggregate equal-weighted (EW) and value-weighted (VW) fund portfolio's industry-neutral size factor beta in month t to forecast different versions of industry-neutral size factor return (*SMB_FF_N, SMB_50_N, SMB_30_N and SMB_20_N*) in month t+1.

Table 15.A

Equal-Weighted	SMB_FF (t+1)	SMB_50 (t+1)	SMB_30 (t+1)	SMB_20 (t+1)
SMB_beta (t)	0.029	0.036	0.046	0.054
	(2.699)	(2.610)	(2.791)	(2.869)
R-square	4.60%	4.30%	4.90%	5.20%
	Control RM-Rf (t+1),HML (t+1),MOM (t+1)			
SMB_beta (t)	0.027	0.034	0.045	0.052
	(2.430)	(2.403)	(2.612)	(2.684)
R-square	6.40%	6.40%	6.90%	7.10%
Value-Weighted	SMB_FF (t+1)	SMB_50 (t+1)	SMB_30 (t+1)	SMB_20 (t+1)
SMB_beta (t)	0.03	0.037	0.048	0.056
	(2.752)	(2.715)	(2.912)	(3.000)
R-square	4.80%	4.70%	5.30%	5.60%
	Control RM-Rf (t+1),HML (t+1),MOM (t+1)			
SMB_beta (t)	0.028	0.035	0.047	0.055
	(2.494)	(2.522)	(2.747)	(2.829)
R-square	6.60%	6.70%	7.40%	7.60%

Table 15.B

Equal-Weighted	SMB_FF_N (t+1)	SMB_50_N (t+1)	SMB_30_N (t+1)	SMB_20_N (t+1)
SMB_beta_N (t)	0.012	0.028	0.021	0.016
	(2.285)	(2.967)	(2.714)	(2.637)
R-square	3.34%	5.51%	4.65%	4.40%
	Control RM-Rf (t+1), HML_FF_N (t+1), MOM (t+1)			
SMB_beta_N (t)	0.010	0.024	0.018	0.013
	(1.904)	(2.536)	(2.292)	(2.217)
R-square	7.51%	10.36%	9.52%	9.57%
Value-Weighted	SMB_FF_N (t+1)	SMB_50_N (t+1)	SMB_30_N (t+1)	SMB_20_N (t+1)
SMB_beta_N (t)	0.012	0.029	0.022	0.016
	(2.267)	(3.010)	(2.756)	(2.698)
R-square	3.29%	5.66%	4.79%	4.60%
	Control RM-Rf (t+1), HML_FF_N (t+1), MOM (t+1)			
SMB_beta_N (t)	0.010	0.025	0.018	0.014
	(1.889)	(2.576)	(2.333)	(2.274)
R-square	7.47%	10.48%	9.64%	9.72%

Robustness Check

A. Chinese Hybrid Stock Mutual Funds and Index Stock Mutual Funds

A.1 Summary Statistics

In Table A.1, our data covers 145 hybrid stock funds during the period of 2003 to 2015. Column 1 records the annual reporting period. Column 2 to 5 report the number of funds, the total AUM of funds, the aggregate stock market capitalization, and the ratio between the two. AUM and MktCap are in RMB billion. Ratios are in %.

In Table A.2, the data covers 698 passive index stock funds during the period of 2003 to 2015. Column 1 records the annual reporting period. Column 2 to 5 report the number of funds, the total AUM of funds, the aggregate stock market capitalization, and the ratio between the two. AUM and MktCap are in RMB billion. Ratios are in %.

In Table A.3, we aggregate similar summary statistics for the 535 stock mutual funds, 145 hybrid stock mutual funds, and 698 passive index stock mutual funds resulting in a total sample of 1378 funds in the period of 2003 to 2015.

Table A.1

Report period	# of Funds	AUM of Funds (bn)	Aggr.Stock Mktcap (bn)	AUM/MktCap
4Q/2003	14	15	1245	1.20%
4Q/2004	38	82	1116	7.35%
4Q/2005	50	69	1020	6.76%
4Q/2006	65	119	2413	4.93%
4Q/2007	77	737	9154	8.05%
4Q/2008	79	360	4540	7.93%
4Q/2009	81	528	15080	3.50%
4Q/2010	83	501	19235	2.60%
4Q/2011	84	368	16520	2.23%
4Q/2012	87	297	18223	1.63%
4Q/2013	89	321	20042	1.60%
4Q/2014	104	295	31562	0.93%
4Q/2015	127	292	41793	0.70%

Table A.2

Report period	# of Funds	AUM of Funds (bn)	Aggr.Stock Mktcap (an)	AUM/MktCap
4Q/2003	1	2	1245	0.16%
4Q/2004	2	3	1116	0.27%
4Q/2005	3	7	1020	0.69%
4Q/2006	8	14	2413	0.58%
4Q/2007	10	78	9154	0.85%
4Q/2008	11	61	4540	1.34%
4Q/2009	20	222	15080	1.47%
4Q/2010	64	339	19235	1.76%
4Q/2011	116	316	16520	1.91%
4Q/2012	193	359	18223	1.97%
4Q/2013	255	427	20042	2.13%
4Q/2014	318	469	31562	1.49%
4Q/2015	628	888	41793	2.12%

Table A.3

Report period	# of Funds	AUM of Funds (bn)	Aggr.Stock Mktcap (bn)	AUM/MktCap
4Q/2003	59	80	1245	6.43%
4Q/2004	87	151	1116	13.53%
4Q/2005	121	164	1020	16.08%
4Q/2006	178	510	2413	21.14%
4Q/2007	212	2330	9154	25.45%
4Q/2008	247	1057	4540	23.28%
4Q/2009	303	1799	15080	11.93%
4Q/2010	401	1829	19235	9.51%
4Q/2011	507	1431	16520	8.66%
4Q/2012	634	1395	18223	7.66%
4Q/2013	724	1506	20042	7.51%
4Q/2014	827	1480	31562	4.69%
4Q/2015	1251	2003	41793	4.79%

A.2 Regression Results for Aggregate Performance Evaluation of Hybrid Stock Mutual Funds

Table A.4 shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the CAPM, FF3F and FF3F+MOM versions of regression (7) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of hybrid stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0. Table A.5 shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (8) (HM) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of actively hybrid stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0. The data cover 145 hybrid stock funds from Jan 2003 to Dec 2015.

Table A.4

	12*alpha	Rm-Rf	SMB	HML	MOM	R-sq
EW						
CAPM	6.32	0.73				0.85
	(2.44)	(-11.16)				
FF3F	10.13	0.78	-0.13	-0.5		0.93
	(5.42)	(-12.34)	(-4.09)	(-12.46)		
FF3F+MOM	9.38	0.78	-0.08	-0.36	0.24	0.95
	(5.84)	(-13.98)	(-2.98)	(-9.81)	(7.24)	
VW						
CAPM	5.13	0.73				0.86
	(1.99)	(-10.88)				
FF3F	9.4	0.79	-0.18	-0.51		0.93
	(5.21)	(-12.1)	(-5.68)	(-12.91)		
FF3F+MOM	8.72	0.79	-0.13	-0.37	0.24	0.94
	(5.50)	(-13.52)	(-4.77)	(-9.29)	(6.74)	

Table A.5

	EW		VW	
	HM_FF3	HM_FF3+MOM	HM_FF3	HM_FF3+MOM
12*Alpha	6.60	4.44	6.17	4.19
	(2.30)	(1.81)	(2.22)	(1.73)
Rm-Rf	0.77	0.77	0.79	0.79
	(-9.09)	(-10.60)	(-9.74)	(-10.64)
SMB	-0.21	-0.19	-0.25	-0.23
	(3.59)	(-3.89)	(-4.37)	(-4.73)
I(SMB>0)*SMB	0.16	0.21	0.14	0.20
	(1.62)	(2.65)	(1.63)	(2.46)
HML	-0.50	-0.34	-0.50	-0.36
	(12.28)	(-8.53)	(-12.73)	(-9.00)
MOM		0.27		0.25
		(7.61)		(7.07)
R-square	0.93	0.95	0.93	0.94

A.3 Placebo Test: Regression Results for Aggregate Performance Evaluation of Passive Index Stock Mutual Funds

Table A.6 shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the CAPM, FF3F and FF3F+MOM versions of regression (7) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of passive index stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0. Table A.7 shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (8) (HM) estimated on the equal-weighted (EW) and value-weighted (VW) net returns on the portfolios of passive index stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0. The data cover 698 passive index stock funds from Jan 2003 to Dec 2015.

Table A.6

	12*alpha	Rm-Rf	SMB	HML	MOM	R-sq
EW						
CAPM	-2.11	0.94				0.96
	(-1.31)	(-3.89)				
FF3F	1.11	0.97	-0.23	-0.17		0.98
	(0.93)	(-2.17)	(-11.22)	(-6.50)		
FF3F+MOM	1.12	0.97	-0.26	-0.17	-0.01	0.98
	(0.93)	(-2.72)	(-10.93)	(-5.66)	(0.43)	
VW						
CAPM	-1.94	0.95				0.94
	(-0.95)	(-2.44)				
FF3F	1.56	0.98	-0.30	-0.08		0.97
	(1.02)	(-1.60)	(-11.35)	(-2.42)		
FF3F+MOM	1.77	0.98	-0.31	-0.12	-0.07	0.97
	-1.16	(-1.70)	(-11.64)	(-3.30)	(-1.67)	

Table A.7

	EW		VW	
	HM_FF3	HM_FF3+MOM	HM_FF3	HM_FF3+MOM
12*Alpha	0.30	0.33	-0.14	-1.20
	(0.16)	(0.20)	(-0.73)	(-0.19)
Rm-Rf	0.97	0.97	0.97	0.97
	(-2.25)	(-2.32)	(-1.98)	(-2.06)
SMB	-0.25	-0.25	-0.37	-0.38
	(-6.52)	(-6.50)	(-7.71)	(-7.89)
I(SMB>0)*SMB	0.03	0.04	0.08	0.07
	(0.57)	(0.56)	(1.53)	(1.60)
HML	-0.17	-0.17	-0.07	-0.11
	(-6.38)	(-5.51)	(-2.32)	(-2.90)
MOM		-0.01		-0.07
		(-0.24)		(-1.90)
R-square	0.98	0.98	0.97	0.97

B. Different Versions of Factor-Timing Model

Table B shows the annualized intercepts of (12*alpha), the slopes of the factors and t-statistics (in parentheses) for the FF3F and FF3F+MOM versions of regression (4) and (5) estimated on the equal-weighted (EW) net returns on the portfolios of actively managed stock mutual funds. For the market slope, t-statistics tests whether b is different from 1 instead of 0. The data cover 535 stock mutual funds from Jan 2003 to Dec 2015.

Table B

	HM_FF3	HM_FF3+MOM	TM_FF3	TM_FF3+MOM
12*Alpha	3.99	2.75	6.90	6.32
	(1.08)	(0.74)	(2.66)	(2.52)
Rm-Rf	0.79	0.8	0.81	0.81
	(-5.48)	(-5.89)	(-9.35)	(-10.53)
I(Rm-Rf>0)*(Rm-Rf)/(Rm-Rf)^2	0.03	0.02	0.07	-0.04
	(0.55)	(0.35)	(0.47)	(-0.32)
SMB	-0.26	-0.24	-0.15	-0.10
	(-3.87)	(-3.88)	(-4.34)	(-3.18)
I(SMB>0)*SMB/SMB^2	0.21	0.25	0.97	1.40
	(1.99)	(2.72)	(1.80)	(2.87)
HML	-0.60	-0.51	-0.57	-0.40
	(-6.85)	(-6.27)	(-12.34)	(-7.78)
I(HML>0)*HML/HML^2	0.05	0.17	-0.08	0.26
	(0.43)	(1.31)	(-0.15)	(0.50)
MOM		0.29		0.27
		(3.67)		(6.38)
I(MOM>0)*MOM/MOM^2		-0.07		-0.58
		(-0.53)		(-0.83)
R-square	0.93	0.94	0.93	0.94

Table C
Out-of-sample Forecasting Results

Table C reports the out-of-sample forecasting results of predictive regressions (17) and (18) using Jan 2003 to June 2008 as the initial estimation period, so that the forecast evaluation period spans over July 2008 to Dec 2015. The R^2_{OS} statistics in percentage are reported.

$$\widehat{SMB\_N}_{t+1} = \widehat{\alpha_{mf}}_t + \widehat{P_{mf}}_t SMB\_pos\_N_{1:t;t}$$

$$\widehat{SMB\_N}_{t+1} = \widehat{\alpha_{mf}}_t + \widehat{b_{mf}}_t SMB\_beta\_N_{1:t;t}$$

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1}(SMB\_N_{t+1} - \widehat{SMB\_N}_{t+1})^2}{\sum_{t=p}^{T-1}(SMB\_N_{t+1} - \overline{SMB\_N_{t+1}})^2}$$

Table C

R-squareOS(%)	SMB_FF_N	SMB_50_N	SMB_30_N	SMB_20_N
EW_SMB_pos_N	4.36%	3.33%	4.13%	3.88%
VW_SMB_pos_N	5.21%	5.52%	7.75%	6.98%
EW_SMB_beta_N	4.43%	6.09%	3.59%	4.19%
VW_SMB_beta_N	5.16%	7.23%	6.27%	4.66%