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Follow the smart money: Factor forecasting in China

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ABSTRACT

We present novel evidence of factor timing in the Chinese stock market. Actively managed Chinese stock mutual funds have larger exposure to the size factor when it performs well and smaller exposure when it performs poorly. By constructing a proxy for the size preference of active stock funds, we can forecast size factor returns in the subsequent periods. A one-standard-deviation increase in the size factor loading of active stock funds is associated with an increase in the size factor return of 1.2% in the next month and 10.8% in the next year. The result is not driven by industry rotation, price impact of mutual funds, or factor momentum. Actively managed stock mutual funds do not appear to time value or momentum factors.

1. Introduction

Factor investing is a common investment approach used to exploit differences in average returns based on stock-level characteristics. Long-short portfolios can be constructed based on these characteristics and rebalanced at regular intervals. Factor investing has become wildly popular in the past two decades, and investors have been exploring new ways to trade factors. Andrew Ang, the Head of Factor-Based Strategies at the world's largest asset manager Blackrock, summarized the importance of factor investing: “Factor investing is the way of the future. It's about empowering investors to deliberately and directly access ideas to help achieve their financial goals.”[1] Blackrock offers factor-focused funds for U.S., global, and emerging markets such as the iShares Factors US Blend Style ETF, iShares Edge MSCI Multifactor Global ETF, and iShares Edge MSCI Multifactor Emerging Markets ETF. China International Capital Corporation (CICC), one of the largest investment banks in China, shares the same vision for the importance of factor investing. CICC published a report on factor investing in January 2020 which states “Factor-focused investment products can deliver investors smart betas that improve investment efficiency.”[2]

Factor timing, changing one's portfolio composition to take advantage of time-varying factor returns, has become topical in recent years as factors such as value and momentum undergo extended periods of poor performance. By exploiting the variation of factor returns over time, factor timing does not require the underlying factors have large and positive unconditional returns. The focus is more on whether the investor can dynamically adjust his portfolio as factor returns wax and wane over time.

Factor-timing evidence from the U.S. equity markets is controversial. On the one hand, Arnott et al. (2016) argue that valuation ratios can be used to forecast factor returns. Factors which are trading at a discount relative to their historical averages can deliver outperformance in the future. On the other hand, Asness (2016a, 2016b) argue against predicting factor returns using valuation

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[1] https://www.blackrock.com/americas-offshore/strategies/what-is-factor-investing

[2] http://stock.finance.sina.com.cn/stock/go.php/vReport_Show/kind/search/rptid/631785742192/index.phtml

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Table 1
Monthly Benchmark Factor Returns in the Chinese Stock Market

2003.01–2017.09	Average Return (%)	Standard Deviation (%)	t-stat
Rm-Rf	0.94	8.47	1.48
SMB_FF	0.74	4.66	2.12
HML_FF	0.69	3.77	2.43
MOM	−0.44	3.98	−1.48
SMB_50	0.84	6.14	1.83
SMB_30	1.16	7.98	1.93
SMB_20	1.35	8.58	2.09

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 used to evaluate mutual fund performance is Jan 2003 to Sept 2017.
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) 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”. Then we form six portfolios by intersecting the momentum 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).
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”.

ratios: such timing strategies have been statistically weak, and some timing strategies may not be implementable in practice.

Whether factor timing is possible remains an open debate, and controversial findings in the factor-timing literature provides fertile grounds for additional investigation. We participate in this debate by providing important new evidence regarding factor timing in an important market. In doing so, we contribute to the factor-timing literature and take a step towards resolving the controversy surrounding this topic.

In this paper, we investigate factor timing in the Chinese stock market, where we find strong evidence of predictability for the size factor. Established in 1990, the Chinese stock market has become the second largest stock market in the world, just after the U.S. stock market. In 2017, total market capitalization reached over 8 trillion USD. In the past two decades, the Chinese mutual fund industry has become more mature and assets have grown steadily. By August 2017, the total assets under management (AUM) of mutual funds reached 1.5 trillion USD. Actively managed stock mutual funds in China have had strong performance; actively managed stock mutual funds have beaten the aggregate stock market and other benchmarks such as the Fama and French (1992); Fama and French, 1993 three-factor model and the Carhart (1997) four-factor model (Chi, 2017). Weighting by fund AUMs, the aggregate active stock mutual fund universe has outperformed the stock market, after fees, by 5.6% per year from 2003 to 2017. In the Chinese stock market, actively managed stock mutual funds behave as sophisticated investors.

In the Chinese stock market, the size factor stands out as one of the most economically significant factors. Table 1 shows that the size factor, SMB_FF, constructed using the same methodology as that of Fama and French (1992), has an average monthly return of 0.74% (t-statistic = 2.12) with a monthly volatility of 4.66%. Its average return is higher than those of value (HML_FF) or momentum (MOM) factors. To further illustrate the large size premium and its robustness, we consider some alternative definitions. SMB_50 is a portfolio that takes long positions in the smallest 50% of all stocks by market capitalization and takes short positions in the largest 50%. SMB_30 and SMB_20 are defined similarly, taking long positions in the smallest 30% (20%) and short positions in the largest 30% (20%). SMB_50, SMB_30, and SMB_20 all have economically large average monthly returns: 0.84% (t = 1.83), 1.16% (t = 1.93), and 1.35% (t = 2.09).

Although the unconditional factor returns are impressive, investors may further improve their investment set if they can opportunistically adjust their exposure to the size factor. Sophisticated investors with the knowledge and resources to time factors could outperform static factor strategies. As actively managed stock mutual funds are considered to be sophisticated investors, we investigate their ability to time factors.

Treynor and Mazuy (1966) and Henriksson and Merton (1981) models are well-known models used to capture market-timing behavior. We extend these models by including factor-timing terms as well as control for common factor exposures. Actively-managed Chinese stock mutual funds exhibit economically and statistically significant timing coefficients on the size factor: the size factor exposure of active stock mutual funds is larger when size performs well. Interestingly, Chinese mutual funds do not appear to time value or momentum factors; neither Treynor and Mazuy (1966) nor Henriksson and Merton (1981) models show significant factor-timing coefficients for value or momentum. Active stock funds do not seem to adjust their exposure to value or momentum dynamically depending on factor returns.

If active stock funds are skilled at factor timing, presumably they would adjust their size exposure to take advantage of this skill. Since active stock funds can time size factor returns, their time-varying size exposure may also be indicative of future size factor returns. We construct a proxy for the size preference of Chinese stock mutual funds using their size factor loadings from the Fama and

French (1992) model. A large size loading indicates a portfolio tilt towards small-cap stocks, whereas a small size loading indicates a tilt towards large-cap stocks. We estimate size loadings using daily data and use the estimated loadings to forecast returns of the size factor in the following month. A one-standard-deviation increase in the size loading is associated with a 1.2% increase in next month size factor returns.

Our analysis of factor timing is corroborated by out-of-sample evidence. We evaluate the out-of-sample (OOS) forecasting performance of active stock funds' size exposure through a comparison to the historical mean. The OOS R-squared of Campbell and Thompson (2008) is 6.5%, indicating that size exposure of active stock funds is a stronger predictor of size factor returns than historical average returns. The Clark and West (2007) mean-squared forecast error (MSFE) adjusted statistic shows the OOS R-squared is not only economically large, but also statistically significant at the 5% level.

We sort our full sample into quartiles based on one-month lagged size exposure of active stock funds. We compute average monthly returns of each quartile and compare them across quartiles. This procedure provides a nonparametric test of the average return differences conditional on lagged size exposure. In the months after the bottom 25% of size exposure, average return to the size factor is −0.52%, which stands in sharp contrast to the average size return in the months after the highest 25% of size exposure, 2.47%. This difference of 2.99% across the extreme quartiles is statistically significant at the 5% level.

Actively managed stock funds that are more skillful at factor timing are able to adjust their size exposure more effectively. We sort actively stock funds into quartiles based on the t-statistic of the factor timing coefficient from the Henriksson and Merton (1981) model, and we compute the size exposure of each quartile. The size exposure of the top 25% in factor-timing ability strongly predicts future size factor returns, whereas the size exposure of the bottom 25% only weakly predicts size factor returns.

Passive index funds and hybrid stock funds serve as control groups for active stock funds. Passive index funds do not exhibit any ability to time the size factor. The factor-timing coefficients in Treynor and Mazuy (1966) and Henriksson and Merton (1981) are economically small and statistically indistinguishable from zero. Hybrid stock funds show some factor-timing behavior, but to a lesser degree than active stock funds.

The ability of active stock fund's ability to time the size factor does not appear to stem from the funds' industry rotation choices. We consider an industry-neutral size factor construction, first sorting on market capitalization within each industry, then value-weighting across industries. The size exposure of active stock funds also forecasts this industry-neutral size factor, indicating our results are not driven by industry-specific forces.

Persistent return predictability suggests that our results are unlikely driven by transitory price effects, such as the price impact of stock mutual funds adjusting their holdings towards or away from small-cap stocks. The size exposure of actively managed stock mutual funds can forecast size factor returns well beyond one month. We trace out the cumulative returns to the size factor after changes in active stock funds' size factor loading, and we find economically large continuations without reversal after 36 months. A one-standard-deviation increase in the size loading is associated with a 10.8% increase in next year's returns.

Gupta and Kelly (2019) demonstrate that strong past factor returns can predict future returns. We control for factor momentum in our forecasting regressions by including lagged size factor returns. The predictive coefficient of mutual funds' size exposure on future size factor returns remains unchanged, and lagged size factor returns do not explain future size factor returns. Factor momentum does not appear to drive our results.

Our paper is related to the literature on factor timing. Much of the existing literature is focused on the U.S. markets. Arnott et al. (2016) make strong arguments that valuations ratios can predict factor returns. Asness (2016a, 2016b) makes strong counter-arguments against using valuation ratios to forecast factor returns and maintains factor timing is difficult at best. Compared to these papers, we offer two contributions. First, we focus on the Chinese stock market, where empirical facts on equity factors are not as complete as those for the U.S. markets. Second, we demonstrate strong evidence of return predictability for the size factor, although we do not find factor predictability for value and momentum.

More broadly, our paper is also related to the literature on market timing. Much like the literature on factor timing, market timing has been a controversial topic. Goyal and Welch (2008) examine 14 different forecasting variables for the U.S. stock market and find these variables cannot beat the historical mean in out-of-sample tests. Cochrane (2008), in contrast, offers a strong argument defending return predictability by jointly examining returns and dividend growth forecasts. Our paper shows that the size factor is also predictable, by following the actions of smart money. Investors who have the resources to implement a factor-timing strategy can benefit from factor timing, as in Hull and Qiao (2017), who illustrate the economic implication of market-timing strategies.

Our paper adds to a booming literature that lies at the intersection of factor investing and institutional-investor behavior. Abbas et al., 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. The authors conclude that hedge funds, rather than mutual funds, serve as smart money in the U.S. market. Our results show that in China, stock mutual funds serve as smart money, as they are able to profitably exploit the size factor's time-series variation. Edelen et al. (2016) examine demand prior to well-known stock return anomalies and find that institutional investors have a strong tendency to buy stocks classified as overvalued (short leg of anomaly factor), and that these stocks have particularly negative ex-post abnormal returns. Moreover, they find that such patterns are strongest at the one-year horizon and are reversed at the quarterly horizon. Using data on Chinese stock mutual funds, we draw different conclusions by establishing a positive predictive relationship between mutual funds' size tilt and future size factor returns and such pattern doesn't have long-term reversal.

Finally, our paper is related to Chen and Chi (2018), who find evidence of factor-timing skill among actively managed stock mutual funds in China. They show that Chinese stock mutual funds have higher exposure to the size factor when small-cap stocks perform better and lower exposure when large-cap stocks perform better. Whereas Chen and Chi (2018) focus on the contemporaneous size exposure of Chinese mutual funds, we consider a forecasting relationship between mutual funds' size tilt and

Table 2.A
Summary statistics of Chinese stock mutual funds

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	15,080	6.96%
4Q/2010	254	989	19,235	5.14%
4Q/2011	307	747	16,520	4.52%
4Q/2012	354	739	18,223	4.06%
4Q/2013	380	758	20,042	3.78%
4Q/2014	405	716	31,562	2.27%
4Q/2015	496	823	41,793	1.97%
4Q/2016	557	683	39,085	1.75%

In Table 2.A we report summary statistics for the actively managed Chinese stock mutual funds. Column 1 reports the annual reporting period. Column 2 reports the number of funds. Columns 3 and 4 report the total AUM of funds and the aggregate Chinese stock market capitalization. Column 5 reports the ratio between column 3 and column 4, i.e. the percentage of stock market capitalization held by the actively managed stock mutual funds. AUM and MktCap are in ¥billion. In Table 2.B, we show the total AUM and percentage of stock market capitalization held by the hybrid stock mutual funds and the passive index stock mutual funds.

future size factor returns. The size loading of aggregate stock mutual funds has significant forecasting power for the size factor return in the following periods. By following smart money and extracting relevant information, we demonstrate a novel approach to forecast factor returns.

2. Data

We collect our stock market and mutual fund data from Wind Financial Terminal (WIND), a leading Chinese financial data provider. Founded in 1994, WIND serves more than 90% of the domestic financial enterprises, including securities firms, mutual funds, insurance companies and banks. Overseas, WIND serves 75% of the Qualified Foreign Institutional Investors (QFII). Our data on mutual funds are free of incubation and survivorship bias.

Our main sample includes 683 actively managed stock mutual funds. These are mutual funds which are required to invest at least 60% (raised to 80% after 2015) of their total assets in the A-share market. Active stock funds represent a substantial portion of the Chinese stock market: in 2007, their aggregate holdings represented 16.6% of the Chinese stock market capitalization. (see Table 2.A) We start our sample period in 2003, because before then there were fewer than 50 stock mutual funds in China. Our sample ends in September 2017. Unless otherwise defined, we use mutual funds' net returns (after management fees) to present our results throughout the paper.

In addition to our main focus of actively managed stock mutual funds, we also construct two other control groups of mutual funds: hybrid stock funds and passive index funds. Hybrid stock funds are only required to hold a minimum of 30% of fund assets in A-share stocks, whereas actively managed stock funds are required to hold a minimum of 60% of fund assets in stocks. Passive index funds track pre-determined stock indices and manage fund assets passively.

Table 2.B
Summary Statistics of Chinese Stock Mutual Funds

	Hybrid Stock Mutual Funds			Index Stock Mutual Funds		
Report period	# of Funds	AUM of Funds (bn)	AUM/MktCap	# of Funds	AUM of Funds (bn)	AUM/MktCap
4Q/2003	45	49	4.03%	3	8	0.64%
4Q/2004	72	123	11.21%	3	7	0.62%
4Q/2005	95	127	12.71%	5	13	1.33%
4Q/2006	153	519	21.90%	11	26	1.09%
4Q/2007	185	2206	24.37%	16	162	1.79%
4Q/2008	219	962	21.66%	17	77	1.74%
4Q/2009	263	1504	10.07%	52	366	2.45%
4Q/2010	310	1396	7.32%	94	382	2.00%
4Q/2011	365	1045	6.40%	149	346	2.12%
4Q/2012	412	1031	5.73%	240	487	2.71%
4Q/2013	437	1020	5.15%	295	419	2.12%
4Q/2014	453	957	3.04%	363	836	2.66%
4Q/2015	497	954	2.30%	682	911	2.19%
4Q/2016	524	767	1.96%	693	856	2.19%

We include summary statistics for the three fund categories in Table 2.A and Table 2.B. By the end of year 2007, the aggregate holding of hybrid stock funds and passive index stock funds represented 24.4% and 1.8% of the Chinese stock market capitalization. In recent years, we observe a steady decline for the percentage of stock market capitalization held by active and hybrid stock funds, while a stable increase for passive index stock funds: by the end of year 2016, the aggregate holding of active stock funds, hybrid stock funds and passive index stock funds represented 1.8%, 2.0% and 2.2% of the Chinese stock market capitalization. While the A-shares market capitalization has increased, the AUM of active stock funds and hybrid stock funds have decreased since 2007.

3. Timing the Size Factor

In this section, we discuss factor-timing evidence of Chinese actively managed stock mutual funds. We extend the market-timing models of Treynor and Mazuy (1966), and Henriksson and Merton (1981) to incorporate the factor-timing terms:

$$R_{mf,t} - R_{ft} = \alpha_{mf}^{TM} + b_{mf}^{TM}(Rm_t - Rf_t) + \gamma_{mf}^{TM} SMB_t SMB_t + s_{mf}^{TM} SMB_t + h_{mf}^{TM} HML_t + \varepsilon_t^{TM} \quad (1)$$

$$R_{mf,t} - R_{ft} = \alpha_{mf}^{HM} + b_{mf}^{HM}(Rm_t - Rf_t) + \gamma_{mf}^{HM} I(SMB_t > 0) SMB_t + s_{mf}^{HM} SMB_t + h_{mf}^{HM} HML_t + \varepsilon_t^{HM} \quad (2)$$

In (1) and (2), $R_{mf,\,t}$ is the return associated with mutual funds. R_{ft} is the risk-free rate captured by the 3-month Chinese household savings deposit rate. Rm_t is the value-weight A-shares market return. SMB_t and HML_t are size and value factor returns constructed using the same methodology as Fama and French (1992) for the A-shares market.

(1) is the augmented Treynor and Mazuy (TM) model and (2) is the augmented Henriksson and Merton (HM) model for the size factor. In order to identify timing ability, we are looking for a significantly positive $\gamma_{mf}{}^{TM}$ under the Treynor and Mazuy model, which measures a positive contemporaneous relationship between the size-factor exposure and the size factor's return. If $\gamma_{mf}{}^{TM}$ is positive, the left-hand portfolio exhibits size-timing ability. Similarly, under the Henriksson and Merton model, a positive $\gamma_{mf}{}^{HM}$ represents a positive contemporaneous relationship between the size-factor exposure and the sign of the size factor's return. If $\gamma_{mf}{}^{HM}$ is positive, mutual funds are able to time the size factor.

While both (1) and (2) measure factor-timing behavior, they have different economic interpretations. If factor-timing ability comes from a fund manager's ability to forecast the magnitude of the size factor return, then fund should increase its aggregate loading on the size factor when it is expected to perform well. In fact, (1) measures timing ability from varying the size factor loading as a linear function of the size factor returns. The effective size loading is $\gamma_{mf}{}^{TM} SMB_t + s_{mf}{}^{TM}$. If factor-timing ability instead comes from fund managers' ability to forecast the direction of the size factor return, mutual funds should increase its aggregate loading on the size factor when the size factor is expected to be positive. (2) measures timing ability from changing the size factor loading depending on the sign of the size factor returns. The factor loading on SMB is $\gamma_{mf}{}^{HM} + s_{mf}{}^{HM}$ if SMB_t is positive and $s_{mf}{}^{HM}$ if SMB_t is negative. A positive $\gamma_{mf}{}^{HM}$ indicates the manager's ability to time the size factor.

In Table 3, we show the regression results for the value-weighted (VW) actively managed stock mutual fund portfolio. Actively

Table 3
Size factor timing of Chinese active stock mutual funds

HM-Style Specification		TM-Style Specification	
$\alpha_{mf}{}^{HM}$	6.21*	$\alpha_{mf}{}^{TM}$	9.16**
	(2.08)		(4.29)
$b_{mf}{}^{HM}$	0.83**	$b_{mf}{}^{TM}$	0.83**
	(−9.24)		(−9.21)
$\gamma_{mf}{}^{HM}$	0.26*		
	(2.53)		
		$\gamma_{mf}{}^{TM}$	0.95*
$s_{mf}{}^{HM}$	−0.33**	$s_{mf}{}^{TM}$	(2.45)
	(−5.29)		−0.19**
			(−5.67)
$h_{mf}{}^{HM}$	−0.58**	$h_{mf}{}^{TM}$	−0.58**
	(−13.74)		(−13.79)
R-squared	0.93		0.93

Table 3 shows the regression coefficients for the HM and TM factor-timing regression (1) and (2) estimated on the value-weighted (VW) net returns on the portfolios of actively managed stock mutual funds.

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

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

The intercepts are shown as annualized percentages (%). T-statistics are in parentheses. For the market slope ($b_{mf}{}^{HM}$ or $b_{mf}{}^{TM}$), the t-statistics test whether b is different from 1 instead of 0. Our sample covers 683 funds from Jan 2003 to Sept 2017. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

managed stock funds have a large-size preference: the coefficient on SMB is negative for both the TM and HM timing models. For both models, mutual funds exhibit a statistically and economically significant factor-timing coefficient. The aggregate fund portfolio's size-factor-timing coefficient is 0.26 ($t = 2.53$) under the HM factor-timing model and 0.95 ($t = 2.45$) under the TM factor-timing model. Our results show that the Chinese actively managed stock mutual funds are successfully timing the size factor. That is, they are increasing small-cap stock holdings when small-caps are outperforming, and vice versa.

Chinese mutual funds do not appear to possess factor-timing ability for value or momentum factors. Table 4 presents TM and HM factor-timing regressions that include factor-timing terms for HML and MOM, in addition to SMB. For each factor, we include a linear term plus a quadratic term for the Treynor and Mazuy (1966) model, and we include a linear term plus a piecewise-linear term for the Henriksson and Merton (1981) model.

We find the TM and HM factor-timing coefficients to be economically small and statistically insignificant. For HML, the HM model exhibits some potential for factor timing, but the point estimate is only about one-third the size of SMB. The TM model does not show any factor timing. For MOM, both the HM and TM models show negative coefficients. Controlling for factor-timing of HML and MOM, the outcome for the factor timing of SMB is unchanged. We still observe large and significant timing coefficients for SMB.

4. Forecasting the Size Factor

Chinese actively managed stock mutual funds appear to be informed investors who dynamically adjust their size exposure. The size-factor preference of these informed investors may reveal future performance of the size factor – their portfolio positioning should forecast future performance of the size factor. To test this idea, we explore the forecasting power of a proxy we construct to capture mutual funds' size tilt.

We construct a simple proxy from mutual funds' daily returns. As mutual funds are required to publicly report their net asset value after market close each day, mutual fund returns are available with minimal delay. Our data source WIND collects and publishes such data daily. For a mutual fund on day t, we estimate its size tilt based on its past 20 trading day's return series using the Fama and French (1992) three-factor model:

$$R_{mf,t} - R_{ft} = \alpha_{mf} + \beta_{rmrf}(Rm_t - Rf_t) + \beta_{smb}SMB_t + \beta_{hml}HML_t + \varepsilon_{mf,t} \tag{3}$$

where $R_{mf,\ t}$ is the mutual fund's return. R_{ft} is the risk-free rate. Rm_t is the value-weight A-shares market return. SMB_t and HML_t are size and value factor returns constructed using the same methodology as Fama and French (1992) for the A-shares market. As the size factor captures the return spread between small-cap and large-cap stocks, a large and positive β_{smb} shows that the mutual fund is holding more small-cap stocks than large-cap stocks. At the end of each month, we estimate β_{smb} for each mutual fund in our sample. We then calculate the value-weighted average β_{smb} from all available actively managed stock mutual funds.

β_{smb} captures the size exposure of active stock funds. To the extent that actively managed stock funds possess information about size factor returns, their size tilt can be informative about the size factor. Motivated by this idea, we use this month's aggregate β_{smb} among all active stock funds to forecast next month's size factor return:

$$SMB_{t+1} = \alpha^{SMB} + b^{SMB}\beta_{smb,t} + e_{t+1} \tag{4}$$

where SMB_{t+1} is the size factor return one month after the measurement of $\beta_{smb,\ t}$. b^{SMB} measures whether the size exposure of active stock funds is informative of future size factor returns. A positive b^{SMB} suggests that active stock funds are informed investors who increase their size exposure ahead of above average SMB returns. A negative b^{SMB} suggests active stock funds do not position their portfolios in such a way to benefit from time variation in the size premium.

Table 5.A shows evidence that the size loading of active stock mutual funds positively predicts next month's size factor returns. SMB_FF is the Fama and French (1992) definition of SMB for A-share. A one-standard-deviation increase in size loading is associated with a 1.18% increase in SMB_FF in the following month. Furthermore, the point estimate of the regression slope is statistically significant at the 1% level. Alternative definitions of size yield the same result: the regression coefficients of SMB_50, SMB_30, or SMB_20 on the size loading of active stock funds are significant at the 5% level, and a one-standard-deviation increase in the size loading is associated with a 0.97%, 1.33%, and 1.53% increase in these size portfolios.

Goyal and Welch (2008), among others, argue that out-of-sample tests are more relevant for assessing genuine return predictability. Out-of-sample tests can also help avoid in-sample over-fitting. Furthermore, out-of-sample tests are less affected by the small-sample size distortions such as the Stambaugh bias and the look-ahead bias concern of the partial least squares approach (Kelly and Pruitt, 2013). We investigate the out-of-sample predictive performance of mutual funds' size factor loading. The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t to forecast $t + 1$ returns. We run out-of-sample analysis by estimating the predictive regression model recursively (Goyal and Welch, 2008; Kelly and Pruitt, 2013) to estimate the predicted SMB returns:

$$S\widehat{M}B_{t+1} = \widehat{\alpha}^{SMB} + \widehat{b}^{SMB}\beta_{smb,t} \tag{5}$$

where $\widehat{\alpha}^{SMB}$ and $\widehat{b}^{SMB}$ are the ordinary least squares estimates from regressing $\{S\widehat{M}B_{s+1}\}_{s=1}^{t-1}$ on a constant and mutual funds' size factor loading proxy $\{\beta_{smb,\ s}\}_{s=1}{}^{t-1}$. Let p be a fixed number chosen for the initial sample training, so that the future expected return can be estimated at $t = p + 1, p + 2, \ldots, T$. Hence, there are $q = T\text{-}p$ out-of-sample evaluation periods. That is, we have q out-of-sample forecasts: $\{SMB_{t+1}\}_{t=p}{}^{T}$. We use the data from July 2003 through December 2008 as the initial estimation period, so that the forecast evaluation period spans over January 2009 through December 2017. The length of the initial in-sample estimation period balances having enough observations for precisely estimating the initial parameters with a relatively long out-of-sample period for forecast evaluation.

We evaluate the out-of-sample forecasting performance based on the Campbell and Thompson (2008)${R_{OS}}^2$ (out-of-sample R^2) statistic, and the Clark and West (2007) MSFE-adjusted statistic. The ${R_{OS}}^2$ statistic measures the proportional reduction in mean squared forecast error for the predictive regression forecast relative to the historical average benchmark:

$$R_{OS}^2 = 1 - \frac{\sum_{t=p}^{T-1} (SMB_{t+1} - \widehat{SMB}_{t+1})^2}{\sum_{t=p}^{T-1} (SMB_{t+1} - \overline{SMB}_{t+1})^2} \tag{6}$$

where $\overline{SMB}_{t+1}$ is the historical average benchmark corresponding to the constant expected return model:

$$\overline{SMB}_{t+1} = \frac{1}{t} \sum_{s=1}^{t} SMB_s \tag{7}$$

The ${R_{OS}}^2$ statistics lies in the range of $(-\infty, 1]$. If the size return forecast, $\widehat{SMB}_{t+1}$, results in the same mean square forecast error as the historical mean $\overline{SMB}_{t+1}$, then the numerator and denominator in (6) are equal and the out-of-sample R^2 would be exactly 0. If the size return forecast achieves lower MSFE than the historical mean, then the ratio in (6) is less than 1 and the OOS R^2 would be positive. Furthermore, if the size return forecasts closely match the realized size return, the numerator would be close to zero and the OOS R^2 would be close to 1. If the size return forecast has higher MSFE than that of the historical mean, then the OOS R^2 would be negative. Goyal and Welch (2008) show that the historical average is difficult to beat out-of-sample, and individual forecasting variables typically fail to outperform the historical average in forecasting the aggregate U.S. stock market.

The MSFE-adjusted statistic of Clark and West (2007) (C−W test) tests the null hypothesis that the historical average MSFE is less than or equal to that of the predictive regression forecast MSFE against the one-sided alternative that the historical average MSFE is greater than that of the predictive regression forecast MSFE. The C−W test corresponds to H_0: ${R_{OS}}^2 \leq 0$ against H_A: ${R_{OS}}^2 > 0$. Clark and West (2007) show that the test statistic has an asymptotically standard normal distribution when we compare different forecasts from nested models.

Intuitively, under the null hypothesis that the constant expected return model is the data-generating process, the predictive regression model produces a noisier forecast than the historical average benchmark because it estimates a slope parameter which has a population value of zero. We thus expect the historical mean MSFE to be smaller than that of the predictive regression model's MSFE under the null hypothesis. If the predictive regression MSFE is truly smaller than that of the historical mean model, the C−W test provides a way to statistically detect this difference.

Table 5.A includes the out-of-sample R^2 and the C−W test statistic. For the Fama and French (1992) construction of SMB, the OOS R^2 is 6.46%, indicating the predictive regression MSFE reduces the historical mean MSFE by 6.46%. OOS R^2 is consistently positive for other size definitions including SMB_50, SMB_30, and SMB_20, with MSFE improvements ranging from 1.4% to 2.5%.

The MSFE-adjusted statistic of Clark and West (2007) has a 95% critical value of 1.645. For SMB_FF, the null is rejected at the 5% level. The predictive regression approach significantly improves against the historical mean in predictive accuracy. This result also holds for SMB_50 and SMB_20, whereas SMB_50 shows a marginally insignificant improvement with a test statistic just below the critical value.

Predictability of size factor returns appears to be associated with long-term permanent price changes in the size factor rather than temporary price impact. Table 5.B reports predictive regressions from 1 month to 24 months. Because of overlapping observations in our regression specification, forecasting regression residuals will be autocorrelated (Hodrick, 1992). We use Newey and West (1986) standard errors to account for the residual autocorrelation. The size exposure of actively managed stock mutual funds not only forecasts next month's returns (k = 1), but also significantly forecasts size factor returns in the next three months, six months, one year, and two years. For each forecast horizon, the predictive coefficient is statistically large with Newey and West (1986) t-statistics ranging from 2.76 to 3.74. R-squared's in the predictive regressions are increasing in the forecast horizon, starting at 5.36% for the one-month forecast and increasing to 38.3% for the 24-month forecast. A one-standard-deviation increase in the size loading is associated with a 3.12% increase in the size factor returns over the next three months and a 10.76% increase over the next 12 months. Persistent long-horizon predictability provides evidence against the possibility that temporary price impact is the driver mutual fund factor-timing ability. We do not observe return reversal even out to 24 months after we observe mutual fund factor loadings.

5. Cross-sectional Dispersion in Timing Skill

In aggregate, actively managed stock mutual funds appear to have some factor-timing ability. These funds increase their size factor loadings just before the size factor outperforms and decrease their size loading before the size factor underperforms. It seems unlikely that all active stock funds possess similar levels of skill, and active stock funds that are more skillful at timing the size factor may also forecast size factor returns better, perhaps due to superior skill or information. We consider cross-sectional variation in mutual funds' factor-timing ability.

Each month, we estimate fund level factor-timing regressions using the augmented Henriksson and Merton (1981) model as in (2). For each fund, we use 36 months for estimation. We sort mutual funds into quartiles based on their t-statistics of the factor-timing coefficient for size, $t({\gamma_{mf}}^{HM})$. The lowest quartile consists of funds that show the worst ability to time size, whereas the highest quartile consists of funds that show the best ability to time size. Within each quartile, we compute the value-weight size exposure of the quartile in the same manner as for the aggregate set of active stock funds. Individual fund size exposures are estimated using daily returns over the past 20 trading days. Individual fund size exposures are combined based on their AUM into a value-weight size exposure for each quartile. We then evaluate the forecasting power of the size exposures of each fund quartile using eq. (4).

Table 5.C presents predictive regressions of eq. (4) for each quartile formed on the t-statistics of the factor-timing coefficient t ($\gamma_{mf}{}^{HM}$). Each panel corresponds to a different quartile portfolio. For active stock funds in the bottom 25% of factor-timing ability, their size exposure does not predict size factor returns in the following month. The predictive coefficient for SMB_FF is 1.47, positive but statistically weak with a t-statistic of 0.67. Furthermore, the size exposure does not capture much variation in size factor returns; the regression R-squared is only 0.34%. In comparison, active stock funds in the top 25% of factor-timing ability have size exposure which is strongly predictive of future size factor returns. The predictive coefficient on SMB_FF from this group is 4.32, with a t-statistic of 3.33. The regression fit is also better with R-squared of 6.32%. For the four fund quartiles, we observe that the predictive coefficient, statistical significance, and regression fit all monotonically increase with fund quartiles' factor-timing ability.

Our findings for SMB_FF also hold for other size definitions. For each of SMB_50, SMB_30, and SMB_20, the predictive coefficient on next month's size factor returns using this month's size exposure increases as a function of the quartile group's factor-timing ability. Statistical significance and R-squared's are also increasing in factor-timing ability. Active stock funds that are better at timing contemporaneous size factor returns also have time-varying size exposures positioned to benefit from the future variation in size factor returns.

6. Quartiles Formed on Size Exposure

Previous sections provide regression evidence that the size exposure of actively managed stock mutual funds can forecast size factor returns in the following months. In this section, we further corroborate the regression evidence by dividing all months into quartiles by mutual funds' size tilt. For our full sample period from January 2003 to September 2017, we calculate a monthly β_{smb} series. We then sort the months (starting from February 2003) into four quartiles based on the signal β_{smb} in the previous month. In contrast to common cross-sectional portfolio sorts using known characteristics, we are forming four groups based on a time series. We calculate the equal-weighted time-series average monthly returns of each quartile. Table 6 reports the results.

For the Fama-French size factor SMB_FF, we see that the bottom-quartile months exhibit an average size factor return of −0.52%, whereas the top-quartile months exhibit an average size factor return of 2.47%. The monthly spread is both economically and statistically significant at 2.99% ($t = 2.50$). When our signal β_{smb} is weakest, active stock mutual funds are positioning their portfolios away from small-cap stocks. In the following month, small-cap stocks on average underperform large-cap stocks by 52 basis points. When our signal β_{smb} is strongest, active stock funds are positioning their portfolios towards small-cap stocks. In the next month, small-cap stocks on average outperform large-cap stocks by 247 basis points. Across the quartiles, average returns are monotonically increasing in the size exposure of active stock funds. As active stock funds shift more assets into small-cap stocks and away from large-cap stocks, small-cap stocks tend to outperform in the following month, and vice versa.

Alternative definitions for the size factor SMB show the same average return pattern as for the Fama and French (1992) definition (SMB_FF). SMB_50, SMB_30, and SMB_20 all have average returns increasing in the previous month's active stock fund size exposure. Their average return spreads between the highest and lowest quartiles have economic magnitudes similar to the spread of SMB_FF: 2.48% for SMB_50, 3.50% for SMB_30, and 4.20% for SMB_20. Although economic significance persists across alternative definitions, the average return spread is not always statistically significance at the 5% level. SMB_50 and SMB_30 have average return spreads between the two extreme quartiles that are significance at the 10% level.

7. Placebo tests

Whereas actively managed stock mutual funds can be considered informed investors who may possess skill in timing the size factor, passive index mutual funds should not be able to time the factor. Passive index funds do not actively manage their size-exposure. Instead, their goal is to minimize tracking error to their pre-determined benchmark index. For this reason, passive index mutual funds serve as a natural candidate for our placebo test – we should not expect to see any timing of the size factor.

Because we do not expect any factor-timing ability from passive index funds, they serve as an ideal control group for actively managed stock mutual funds. We estimate the augmented Treynor and Mazuy (1966) and Henriksson and Merton (1981) factor-timing regressions (1) and (2) for passive index funds. Our sample includes 836 passive index mutual funds. We follow the same approach as for the active stock funds in constructing the value-weight aggregate passive index fund returns. Table 7 contains the factor-timing results.

Controlling for the Fama and French (1992) factors, passive index funds do not have positive alphas. Passive index funds have more neutral factor exposures compared to actively stock funds. The market beta of passive index funds is close to 1 under both the Henriksson and Merton (1981) and Treynor and Mazuy (1966) specifications. The market beta of active stock funds shown in Table 3 is significantly less than 1. Passive index funds also have a smaller value tilt compared to actively managed stock funds.

The augmented Henriksson and Merton (1981) model yields a factor-timing coefficient of just 0.08 for size with a t-statistic of 1.33. This estimate is economically small and statistically indistinguishable from zero. Similarly, for the augmented Treynor and Mazuy (1966) model, the factor-timing coefficient estimate is 0.30 with a t-statistic of 1.20. Indeed, passive index funds do not appear to adjust their size exposure contemporaneously with size factor returns. In comparison, active stock mutual funds have large and positive factor-timing coefficients three times as large as those of passive index funds. The HM estimate is 0.26 ($t = 2.53$) and the TM estimate is 0.95 ($t = 2.45$).

Table 4
Factor timing: A kitchen-sink approach

HM-Style Specification		TM-Style Specification	
$\alpha_{KS}{}^{HM}$	4.92	$\alpha_{KS}{}^{TM}$	9.41**
	(1.53)		(4.47)
$\beta_{KS,\ 1}{}^{HM}$	0.83**	$\beta_{KS,\ 1}{}^{TM}$	0.81**
	(−5.66)		(−11.10)
$\gamma_{KS,\ 1}{}^{HM}$	−0.02		
	(−0.49)		
		$\gamma_{KS,\ 1}{}^{TM}$	−0.11
			(−1.03)
$\beta_{KS,\ 2}{}^{HM}$	−0.25**	$\beta_{KS,\ 2}{}^{TM}$	−0.08*
	(−4.20)		(−2.49)
$\gamma_{KS,\ 2}{}^{HM}$	0.31**		
	(3.03)		
		$\gamma_{KS,\ 2}{}^{TM}$	1.71**
			(3.63)
$\beta_{KS,\ 3}{}^{HM}$	−0.46**	$\beta_{KS,\ 3}{}^{TM}$	−0.37**
	(−5.73)		(−7.57)
$\gamma_{KS,\ 3}{}^{HM}$	0.12		
	(1.03)		
		$\gamma_{KS,\ 3}{}^{TM}$	0.01
			(0.11)
$\beta_{KS,\ 4}{}^{HM}$	0.30**	$\beta_{KS,\ 4}{}^{TM}$	0.31**
	(4.32)		(7.47)
$\gamma_{KS,\ 4}{}^{HM}$	−0.02		
	(−0.14)		
		$\gamma_{KS,\ 4}{}^{TM}$	−0.54
			(−0.86)
R-squared	0.94		0.94

Table 4 shows the regression coefficients of the HM and TM regressions including factor-timing terms for all the factors. We use four risk factors of for the Chinese stock market: $f_1 = Rm - Rf, f_2 = SMB, f_3 = HML, f_4 = MOM$. The regressions are estimated on the value-weighted (VW) net returns on the portfolios of actively managed stock mutual funds.

$$R_{mf,t} - R_{ft} = \alpha_{KS}^{HM} + \sum_{j=1}^{J} \beta_{KS,j}^{HM} f_{j,t} + \sum_{j=1}^{J} \gamma_{KS,j}^{HM} I(f_{j,t} > 0) f_{j,t} + \varepsilon_{KS,t}^{\mathrm{HM}}.$$

$$R_{mf,t} - R_{ft} = \alpha_{KS}^{TM} + \sum_{j=1}^{J} \beta_{KS,j}^{TM} f_{j,t} + \sum_{j=1}^{J} \gamma_{KS,j}^{TM} f_{j,t}^2 + \varepsilon_{KS,t}^{\mathrm{TM}},$$

T-statistics are shown in parentheses. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis. For the market slope, t-statistics tests whether b is different from 1 instead of 0. Our sample covers 683 stock mutual funds from Jan 2003 to Sept 2017.

We also consider hybrid stock mutual funds as a comparison group to actively managed stock mutual funds. Hybrid funds serve as an intermediate group between the actively managed stock mutual funds and the passive index stock mutual funds. Hybrid funds have more flexibility in how much of the fund assets to invest into stocks. In contrast to actively managed stock mutual funds that are required to hold at least 60% of fund assets in stocks, stock hybrid funds are only required to hold at least 30% of fund assets in stocks. Unlike passive index funds, hybrid funds do not necessarily track pre-determined indices.

Hybrid stock funds have a lesser focus on stock investing compared to active stock funds, so we expect them to have less factor-timing skill. We estimate augmented Treynor and Mazuy (1966) and Henriksson and Merton (1981) factor-timing regressions for hybrid stock funds. Our sample includes 586 funds. We use the same approach to construct the value-weight aggregate hybrid stock fund returns as the approach for active stock funds. Table 8 reports the results.

Hybrid stock funds behave more similarly to active stock funds than passive index funds. Hybrid stock funds have economically large alphas beyond the Fama and French (1992) factors and factor-timing terms for SMB. The remaining outperformance is 6.17% or 8.13%, similar in magnitude to the outperformance observed for active stock funds. Furthermore, market, size, and value exposures of hybrid funds are all similar to those of active stock funds. In particular, both hybrid funds and active funds have market betas less than 1, and a bias towards large growth stocks on average.

Factor-timing behavior of hybrid stock funds somewhat resembles that of active stock funds. The Henriksson and Merton (1981) model shows a factor-timing coefficient of 0.14 for SMB, with a t-statistic of 1.63. The Treynor and Mazuy (1966) model shows a factor-timing coefficient of 0.63, which has a t-statistic of 1.78. The point estimates for factor-timing are indeed between the estimates for passive index funds and active stock funds; the factor-timing coefficients for active stock funds are 1.5 to 2 times those of hybrid stock funds, and the factor-timing coefficients for hybrid funds are about twice as large as those of passive funds.

Table 5.A
Forecast size factor returns with lagged mutual fund size beta.

VW SMB_Beta	SMB_FF	SMB_50	SMB_30	SMB_20
b^{SMB} (%)	3.76**	3.09*	4.24*	4.86*
Economic Significance (%)	1.18	0.97	1.33	1.53
t (b^{SMB})	3.14	2.11	2.23	2.38
R-squared (%)	5.36	2.49	2.77	3.77
Out-of-Sample R-squared (%)	6.46	1.39	1.91	2.54
C-W test	2.73	1.58	1.68	1.82

We report the slopes of the β_{smb} and t-statistics for the forecasting regression:

$$SMB_{t+1} = \alpha^{SMB} + b^{SMB}\beta_{smb,t} + e_{t+1}$$

We use the aggregate value-weighted (VW) fund portfolio's size factor beta in month t to forecast different versions of size factor (*SMB_FF, SMB_50,SMB_30 and SMB_20*) in month $t + 1$. We report the economic significance of the slope, which represents the percentage-point change of size factor returns in month $t + 1$ related to a one-standard-deviation change of β_{smb} in month t. We show out-of-sample forecasting results by using Jan 2003 to Dec 2008 as the estimation period, and Jan 2008 to Sept 2017 as the forecasting period. ${R_{os}}^2$ is the Campbell and Thompson (2008) out-of-sample R^2 calculated as

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

where $\widehat{SMB}_{t+1} = \widehat{\alpha}^{SMB} + \widehat{b}^{SMB}\beta_{smb,t}$ and $\overline{SMB}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} SMB_s$. C—W test is the Clark and West (2007) MSFE-adjusted statistic is also shown.

Table 5.B
Forecast Size Factor Returns with Lagged Mutual Fund Size Beta.

	VW SMB_Beta: SMB_FF			
	b_k^{SMB} (%)	Economic Significance (%)	t (b_k^{SMB})	R-squared (%)
k = 1	3.76**	1.18	3.14	5.36
k = 3	10.41**	3.12	2.76	9.77
k = 6	21.66**	6.56	3.74	21.02
k = 12	35.08**	10.76	3.50	31.23
k = 24	50.96**	16.48	3.27	38.30

Table 5.B reports forecasting results for horizons ranging from one month to 24 months. Due to the overlapping nature of our regression specification, we use Newey-West adjusted standard errors to calculate t-statistics.

$$SMB_{t+1\to t+k} = \alpha_k^{SMB} + b_k^{SMB}\beta_{smb,t} + e_{t+1\to t+k}.$$

We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

8. Robustness

We have argued that actively managed stock mutual funds have factor-timing skill that allows the funds to position their size exposure to benefit from future size factor returns. In this section, we consider additional tests to rule out possible alternative explanations related to industry rotation, factor momentum, and liquidity.

One potential concern with our interpretation of the results is that perhaps predictability of size loadings for future size factor returns is a byproduct of industry rotation. Active stock funds dynamically overweight and underweight certain industries, and if that choice is correlated with both changes in market capitalizations of constituent stocks and future size factor returns, we could observe time-varying size loadings for active stock funds that can forecast future size factor returns.

To address the concern, we construct industry-neutral size and value factors and repeat our predictability analysis. We sort stocks by their market capitalization and book-to-market ratios within each of the 24 industries classified by the Global Industry Classification Standard (GICS) to construct industry-specific size and value factors. The industry factors are then value-weighted across industries. Rather than possibly some industries being disproportionately represented in the factors, this procedure allows each industry to be represented proportionally to its market capitalization in the size and value factors. The industry-neutral size factor SMB_FF_N behaves similarly to the unconstrained SMB_FF: SMB_FF_N has an average monthly return of 0.62% and monthly volatility

Table 5.C
Forecast Size Factor Returns with Lagged Mutual Fund Size Beta

	SMB_FF	SMB_50	SMB_30	SMB_20
	1-Low (< 25%)			
β_{smb_mf}	1.47	0.75	1.42	1.85
	(0.67)	(0.28)	(0.41)	(0.49)
R-squared (%)	0.34	0.06	0.12	0.18
	2 (25%–50%)			
β_{smb_mf}	2.68	2.46	3.13	3.75
	(2.22)	(1.66)	(1.79)	(1.92)
R-squared (%)	3.63	1.61	1.87	2.14
	3 (50%–75%)			
β_{smb_mf}	3.46	2.93	3.65	4.57
	(2.85)	(1.91)	(2.06)	(2.22)
R-squared (%)	4.62	2.13	2.47	2.86
	4-High (75%–100%)			
β_{smb_mf}	4.32	3.81	4.99	5.59
	(3.33)	(2.41)	(2.66)	(2.84)
R-squared (%)	6.32	2.31	2.71	3.34

In Table 5.C, we analyze the cross-sectional difference of forecasting power for funds with different timing skills. 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 HM factor-timing regression (2) using their past 36-month returns. Then in each quartile portfolio, we follow the procedure in Table 5.A to get the value-weighted (VW) estimated β_{smb_mf} and run the forecasting regression. We report the slopes of the (β_{smb_mf}) size beta and *t*-statistics (in parentheses). Each panel corresponds to a different quartile. 1-Low indicates the least skilled 25% of funds in factor timing, whereas 4-High indicates the 25% most skilled funds in factor timing.

Table 6
Quartiles formed on lagged size factor loading

	SMB_FF	SMB_50	SMB_30	SMB_20
1-Low	−0.52	−0.61	−0.82	−0.89
	(−0.62)	(−0.66)	(−0.67)	(−0.93)
2	0.79	0.89	1.24	1.33
	(1.04)	(1.02)	(1.10)	(1.14)
3	1.26*	1.19	1.48	1.41
	(2.34)	(1.70)	(1.72)	(1.77)
4-High	2.47**	1.87	2.68	3.31*
	(2.90)	(1.83)	(1.78)	(2.07)
High-Low	2.99**	2.48	3.50	4.20*
	(2.50)	(1.78)	(1.90)	(2.39)

In Table 6, we sort the months from Jan 2003 to Sept 2017 based on the one-month lagged value-weight β_{smb} of active stock funds into four portfolios. In each quartile, we report the average monthly size-factor returns and their t-statistics in parentheses. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

of 3.6%, compared to 0.74% average returns and 4.6% monthly volatility for SMB_FF. The correlation between SMB_FF_N and SMB_FF is 82%. We also construct SMB_50_N, SMB_30_N, and SMB_20_N following the same procedure.

We analyze the predictability of SMB_FF_N following the same methodology as for SMB_FF. Size exposure for the aggregate active stock funds is estimated using the Fama and French (1992) model as in eq. (3). We forecast future size factor returns as in eq. (4) and we report out-of-sample R-squared and the Clark and West (2007) MSFE-adjusted statistics as in eqs. (5) to (7) in Table 9.

Table 9 is the industry-neutral counterpart to Table 5.A. The predictive coefficient of size exposure on next month's SMB_FF_N is 1.80, statistically significant at the 1% level. For a one-standard-deviation increase in the size exposure of active stock funds, SMB_FF_N is expected to be 0.81% higher in the following month. The predictive coefficient and economic magnitude are large, although they are somewhat smaller compared to those for the unconstrained size factor SMB_FF (predictive coefficient 3.76, 1.2% increase in SMB_FF return following a one-standard-deviation increase in size exposure). The OSS R-squared for SMB_FF_N is 6.32%, and the Clark and West (2007) test statistic is 2.89, significant at the 1% level. Both the OOS R-squared and the C—W test statistic are similar in magnitude to those for SMB_FF.

SMB_50_N, SMB_30_N, and SMB_20_N are alternative industry-neutral size factors we include in our analysis. For each of these factors, we observe statistically significant predictive coefficients from lagged size exposure, as well as economically large changes in expected returns following a one-standard-deviation increase in size exposure which ranges from 0.73% to 0.86%. The OOS R-squared are positive for all three alternative size definitions, although they are smaller compared to the OOS R-squared for SMB_FF_N. OOS R-squared and C—W test statistics are very close to those of the unconstrained factors SMB_50, SMB_30, and SMB_20.

We want to rule out liquidity-related explanations that active stock fund's factor-timing behavior is due to temporary price impact from flows towards small-cap stocks. If active stock funds collectively make up sufficient trading volume, it is possible their

Table 7
Placebo test: Passive index funds

Passive Index Funds			
HM-Style Specification		TM-Style Specification	
${\alpha_{mf}}^{HM}$	−0.62	${\alpha_{mf}}^{TM}$	0.34
	(−0.35)		(0.22)
${b_{mf}}^{HM}$	0.98	${b_{mf}}^{TM}$	0.98
	(−1.04)		(−1.22)
${\gamma_{mf}}^{HM}$	0.08	${\gamma_{mf}}^{TM}$	0.30
	(1.33)		(1.20)
${s_{mf}}^{HM}$	−0.40**	${s_{mf}}^{TM}$	−0.33**
	(−8.46)		(−12.61)
${h_{mf}}^{HM}$	−0.10**	${h_{mf}}^{TM}$	−0.11**
	(−3.23)		(−3.26)
R-squared	0.97		0.97

Table 7 reports the regression coefficients for the augmented HM and TM factor-timing regressions (1) and (2) estimated on the value-weighted (VW) net returns of passive index stock mutual funds.

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

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

The intercepts are shown as annualized percentages (%). T-statistics are in parentheses. For the market slope (${b_{mf}}^{HM}$ or ${b_{mf}}^{TM}$), the t-statistics test whether b is different from 1 instead of 0. Our sample covers 836 passive index stock funds from Jan 2003 to Sept 2017. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

Table 8
Placebo test: Hybrid stock mutual funds

Hybrid Stock Funds			
HM-Style Specification		TM-Style Specification	
${\alpha_{mf}}^{HM}$	6.17*	${\alpha_{mf}}^{TM}$	8.13**
	(2.22)		(2.77)
${b_{mf}}^{HM}$	0.79**	${b_{mf}}^{TM}$	0.79**
	(−9.74)		(−9.91)
${\gamma_{mf}}^{HM}$	0.14	${\gamma_{mf}}^{TM}$	0.63
	(1.63)		(1.78)
${s_{mf}}^{HM}$	−0.25**	${s_{mf}}^{TM}$	−0.15**
	(−4.37)		(−4.76)
${h_{mf}}^{HM}$	−0.50**	${h_{mf}}^{TM}$	−0.52**
	(−12.73)		(−12.33)
R-squared	0.93		0.93

Table 8 reports the regression coefficients for the augmented HM and TM factor-timing regressions (1) and (2) estimated on the value-weighted (VW) net returns of hybrid stock mutual funds.

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

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

The intercepts are shown as annualized percentages (%). T-statistics are in parentheses. For the market slope (${b_{mf}}^{HM}$ or ${b_{mf}}^{TM}$), the t-statistics test whether b is different from 1 instead of 0. Our sample covers 586 hybrid stock funds from Jan 2003 to Sept 2017. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

preference towards or away from small-cap stocks will temporary drive returns up or down in the short term. If this is the case, size factor return predictability from lagged size exposure may be just a measure of trading activity of active stock funds.

To differentiate between informed trading and temporary price impact, we examine impulse response function from the impact of one-standard-deviation change in active stock funds' size loading. If future size factor returns are higher due to price impact, we

Table 9
Forecasting industry-neutral size factor returns

	SMB_FF_N	SMB_50_N	SMB_30_N	SMB_20_N
b_N^{SMB} (%)	1.80**	1.61*	1.89*	1.87*
Economic Significance (%)	0.81	0.73	0.86	0.85
t (b_N^{SMB})	3.32	2.38	2.29	2.24
R-squared (%)	5.78	3.15	2.93	2.80
Out-of-Sample R-square (%)	6.32	1.59	1.69	1.57
C-W test	2.89	1.86	1.74	1.52

Table 9 reports the results of the regression on forecasting the industry-neutral size factor returns:

$$SMB\_N_{t+1} = \alpha_N^{SMB} + b_N^{SMB}\beta_{smb\_N,t} + e_{t+1}.$$

We use our aggregate value-weighted (VW) estimated industry-neutral size beta (β_{smb_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 $t + 1$. We report the slopes of β_{smb_N}, its economic significance and t-statistics (in parentheses). The economic significance represents the percentage change of industry-neutral size factor returns in month $t + 1$ related to a one-standard-deviation change of β_{smb_N} in month t. We also show out-of-sample forecasting result by using Jan 2003 to Dec 2008 as the estimation period, and Jan 2008 to Sept 2017 as the forecasting period. R_{os}^2 is the Campbell and Thompson (2008) out-of-sample R^2 and C—W test is the Clark and West (2007) MSFE-adjusted statistic. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

Table 10
Forecasting size factor returns controlling for lagged size factor returns

	SMB_FF		SMB_50		SMB_30		SMB_20	
a_{mf}^{SMB}	0.96*	1.03**	0.99*	1.13*	1.31*	1.52**	1.46*	1.71**
	(2.40)	(2.67)	(2.04)	(2.52)	(2.09)	(2.63)	(2.15)	(2.79)
b_{mf}^{SMB}	3.80**	3.05*	3.98*	2.73	5.22*	3.55	5.68*	3.77*
	(2.86)	(2.38)	(2.46)	(1.85)	(2.49)	(1.93)	(2.52)	(2.04)
c	0.06	0.08	−0.01	0.03	0.01	0.06	0.01	0.07
	(0.74)	(1.10)	(−0.06)	(0.39)	(0.07)	(0.55)	(0.09)	(0.60)
d	0.00	0.03	−0.05	0.00	−0.05	0.01	−0.03	0.04
	(0.02)	(0.42)	(−0.54)	(−0.05)	(−0.44)	(0.07)	(−0.21)	(0.36)
e	−0.11	−0.06	−0.19*	−0.11	−0.24*	−0.14	−0.24	−0.12
	(−1.46)	(−0.84)	(−2.06)	(−1.31)	(−2.02)	(−1.26)	(−1.82)	(−1.02)
f		0.11**		0.18**		0.23**		0.25**
		(2.62)		(3.51)		(3.45)		(3.56)
g		−0.38**		−0.64**		−0.86**		−0.98**
		(−3.89)		(−5.61)		(−5.86)		(−6.33)
R-squared (%)	6.58	16.18	5.08	22.74	5.16	23.71	4.95	25.65

Table 10 reports the slopes of the β_{smb} and t-statistics (in parentheses) for the following multivariate forecasting regression:

$$SMB_{t+1} = a_{mf}^{SMB} + b_{mf}^{SMB}\beta_{smb,t} + cSMB_t + dSMB_{t-1} + eSMB_{t-2} + fRmRf_{t+1} + gHML_{t+1} + e_{t+1}$$

We use our aggregate 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 $t + 1$ and control for the lagged size factor returns and other contemporaneous Fama-French factor returns. We show a single asterisk (*) for coefficients that are significant on a 5% two-tail test basis and double asterisks (**) for coefficients that are significant on a 1% basis.

would expect cumulative returns to be high in the short term but eventually reverse. If stock funds are informed investors who can forecast future size factor returns, we would expect the price changes to be permanent and no return reversal even in the long term.

Fig. 1 shows the cumulative returns after a one-standard-deviation increase in size loading. We see a steady increase in cumulative returns from one month through 36 months. We do not observe any decrease in cumulative returns at any point in time, which would correspond to return reversal. Fig. 2 shows the individual monthly returns for the size factor after a one-standard-deviation increase in size factor loading. If there is any return reversal, some months should show negative average returns. Average monthly returns after the size factor loading increase are consistently positive and decline with horizon, converging towards zero after about 33 months. The lack of return reversal provides evidence that predictability of future size factor returns using active stock funds' size exposure does not appear to be driven by the price impact of active stock funds trading small-cap stocks.

Another potential concern with our findings is the possibility that active stock funds adjust their size exposure based on past size factor returns, rather than forward-looking size factor returns. Active stock fund may simply be following “factor momentum” strategies which increases factor exposure after a period of good performance (Gupta and Kelly, 2019). Past size factor return is the omitted variable that would explain both larger size loadings in the current month and higher size factor returns in the following

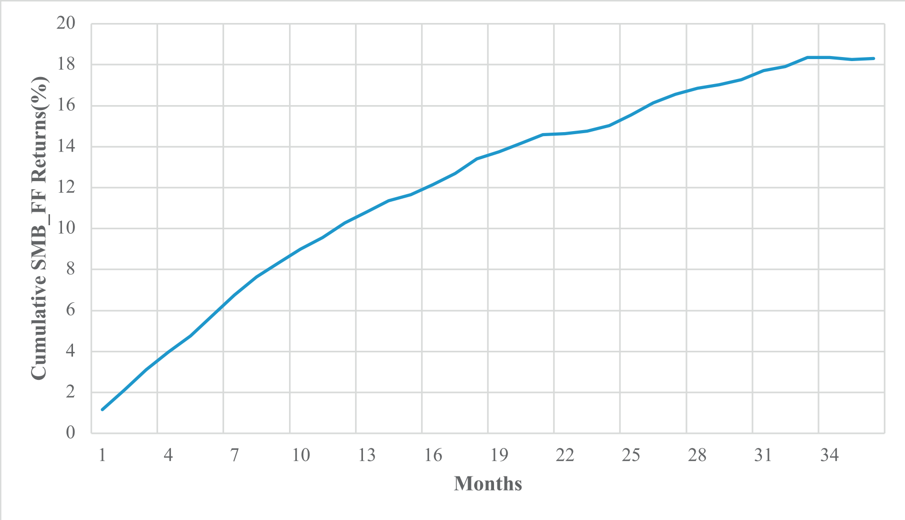

Fig. 1. Cumulative SMB Returns after a One-Standard-Deviation Increase in SMB Loading.
We trace out the cumulative returns (%) of the size factor constructed using the Fama and French (1992) methodology, SMB_FF, after a one-standard-deviation increase in the size exposure of actively managed stock mutual funds, from one month through 36 months. Our sample is from Jan 2003 to Sept 2017.

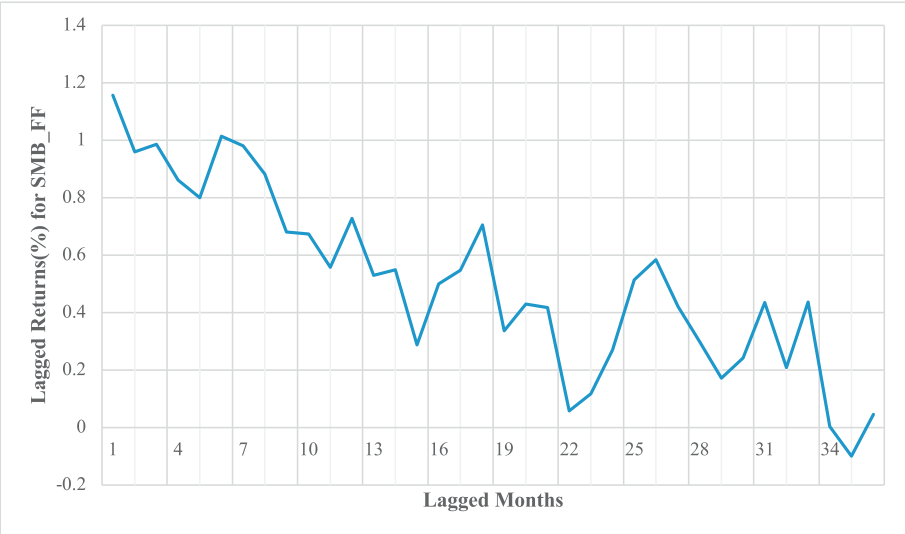

Fig. 2. Monthly SMB Returns after a One-standard-deviation Increase in SMB Loading.
We trace out the individual monthly returns (%) of the size factor constructed using the Fama and French (1992) methodology, SMB_FF, after a one-standard-deviation increase in the size exposure of actively managed stock mutual funds, from one month through 36 months. Our sample is from Jan 2003 to Sept 2017.

month.

In Table 10, we control for lagged size factor returns in the predictability regressions. To predict next month's size factor returns, we include not only the current month's size exposure of active stock funds, but also lagged size factor returns up to three months. Lagged size factor returns do not explain future size factor returns; the coefficients on lagged size factor returns are generally economically and statistically small. The predictive coefficient of size exposure on future size factor returns is almost unchanged compared to Table 5.A, where we do not include past size factor returns. We also include the current period market excess returns and value factor returns in a second specification. Adding these somewhat weakens the predictive coefficient of size exposure on future size factor returns, but they are still economically and statistically large.

9. Conclusion

Our paper demonstrates that Chinese actively managed stock mutual funds can successfully time the size factor. In factor-timing regressions, the size-factor-timing coefficient is economically large and statistically significant for the value-weight portfolio of active stock mutual funds. Size exposures of active stock funds can forecast future size factor returns: a one-standard-deviation increase in size loading is associated with a 1.2% increase in the following month's size factor returns. The forecasting power of our proposed signal is both economically and statistically significant.

We compare passive index funds and hybrid stock funds against active stock funds and find results consistent with fund mandates. Passive index funds do not show any factor-timing ability, whereas hybrid stock funds show weak factor-timing ability. We rule out three alternative explanations of size predictability: 1) industry rotation of active stock funds, 2) price impact of active stock funds buying up small-cap stocks, and 3) size factor momentum. Our findings are most consistent with the interpretation that active stock funds are informed investors who adjust their size exposure conditional on time-varying size factor returns.

Our findings could be related to the structure of the Chinese stock market. Chinese financial markets are known for the prevalence of "guanxi", or connections, and weak legal institutions (Gu et al., 2019), and mutual fund managers can gain informational advantage by exploiting their connections. Stock selection at mutual funds benefit from connections to brokerages and the size of their accounts (Li et al., 2019). Firms strategically link themselves to favorable analysts whose reviews may affect mutual fund investment decisions (Li et al., 2020). All of these channels may influence how Chinese mutual funds adjust their size exposure over time. We leave the identification of specific channels to future studies.

Due to its relatively young age and the presence of a large fraction of retail traders, the Chinese stock market is arguably less efficient than more developed markets. Consequently, institutional investors such as mutual funds and hedge funds can more easily outperform the market. Our study suggests that Chinese stock mutual funds possess skill in timing the size factor and their size exposure can predict future size factor returns. It would be interesting to study information acquisition and production of actively managed stock mutual funds. Why are they informed investors, and how do they determine time-varying size factor returns? As the Chinese stock market matures and smart beta strategies become more commonplace, it remains to be seen whether factor-timing skill of active stock funds will persist in the future.

Credit Author Statement

Yeguang Chi, Qinhua Chen, and Xiao Qiao have all been involved in key stages of the project, including research idea conceptualization and formulation, data gathering and analysis, manuscript writing, editing, and revision.

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