A Kalman filter approach to Chinese mutual funds' market timing abilities

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A KALMAN FILTER APPROACH TO CHINESE MUTUAL FUNDS' MARKET TIMING ABILITIES

WON KYUNG SUB

Nanyang Business School

**A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Master of Business**

2020

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Summary

This paper examines the Kalman filter model's abilities to capture the market timing skills of Chinese mutual fund managers. The Kalman filter approach provides a useful measure of timing skills since it allows for estimation of time series of portfolio beta. Using this measure, I compare the performance of the Kalman filter to that of the OLS-based market timing models developed by Treynor and Mazuy (1966) (TM) and Henriksson and Merton (1981) (HM). The three models are first applied to the Chinese stock size deciles where their return patterns show no timing skills. The finding is that the Kalman filter model produces the false positives approximately at the corresponding significance level while the OLS-based models generate the false positives at too high rate. This implies that the Kalman filter model performs better in detecting the manager's timing skills. Based on this idea, the TM, HM, and Kalman models are applied to the monthly return data of Chinese mutual funds. While the TM and HM models detect the significant timing skills in the period 2014-2018, the four-factor Kalman filter captures the significant market timing behavior in Chinese mutual funds during the periods 2006-2010 and 2014-2018. Based on the false positive tests on the Chinese stock size deciles, the results from the four-factor Kalman filter is more reliable.

1. Introduction

A debate about whether fund managers can time risk factors to generate significant return has been of considerable interest to both academics and practitioners. To the former, significant return implies the violation of Efficient Market Hypothesis, which forms a basis of modern theory of finance. To the latter, it provides a useful barometer whether superior forecasting abilities are due to appropriate selection of securities or timely entrance/exit into/from stock markets. Disentanglement of the two source of forecasting abilities is important since the misjudgment of one ability may result in bias in the other and guide the managers in the wrong direction.

In an attempt to isolate the market timing skills from the securities selection skills, Treynor and Mazuy (1966) (TM, hereafter) and Henriksson and Merton (1981) (HM, hereafter) add constant and convex terms to standard Capital Asset Pricing Model (CAPM). They argue that their convex terms capture the fund managers' market timing skills since a manager with the successful timing skills will increase their exposure to the market factor when the excess market return is high or greater than zero. However, Jagannathan and Korajczyk (1986) argue that fund returns themselves sometimes exhibit option-like patterns that lead to a nonlinear relation between fund and market returns even without active market timing behavior of fund managers. Moreover, Mamaysky et al. (2008) point out the ordinary least square (OLS) return-based models generically have a mis-specified model problem in the study of the managed portfolio return time series because of its static factor loadings assumption. In order to address this problem, Mamaysky et al. (2008) develop the Kalman filter model that allows for dynamic betas and produce statistically more reliable results with regard to the monthly timing skills of the U.S fund managers.

This article follows the framework of Mamaysky et al. (2008) to investigate whether the Kalman filter approach performs better than the traditional TM and HM models in detecting the market timing abilities of Chinese fund managers. To see this, I compare the proportion of false

positives generated by each of the three different models. The monthly return data of Chinese stocks is sorted into 4-years windows and size deciles to create 40 groups of portfolios that do not exhibit market timing abilities. While the one-factor and four-factor TM and HM models approximately produce 20% of significant timing coefficients at the 10% level, the Kalman filter model produces approximately 10% of significant timing coefficients at the 10% level. This implies that the Kalman filter model is more appropriate for the assessment of the market timing abilities in monthly data.

In detecting the timing abilities, the Kalman filter framework has a few advantages over the traditional TM and HM models. Firstly, the Kalman filter model provides a more natural measure of market timing abilities. Market timing abilities refer to a market return forecasting skill where fund managers generate returns by increasing their loading on the market factor when the market return is high and reduce their loading when the market return is low. The Kalman filter approach produces a time series of portfolio betas which allows for measuring market timing abilities as the correlation between time series of portfolio betas and excess market returns. Thus, the Kalman filter model is more appropriate to measure market timing abilities. However, it is difficult to use this measure in the TM and HM models since these OLS return-based models produce static betas.

Secondly, the Kalman filter model does not require portfolio holding information. To overcome the shortcomings of TM and HM models, Jiang, Yao, and Yu (2007) use an alternative market timing measure based on mutual funds' portfolio holding. Using the holding-based measure, they find that actively managed U.S. domestic equity funds on average have positive timing ability, which is in contrast with previous studies. Despite the accuracy of holding-based measure, it is hard to apply these holding-based measures to Chinese stock markets because Chinese funds report their portfolio holdings only semiannually. Thus, the Kalman filter methods can be more appealing when examining Chinese mutual funds timing abilities.

This article contributes to the Chinese mutual fund performance literature. Chen and Chi (2018)

find strong evidence that Chinese mutual funds have successful size-factor timing ability. They argue that size-factor timing explains over 50 percent of Chinese fund alpha. Yi et al. (2019) extend the scope of factor analysis to volatility and liquidity: Chinese mutual funds also significantly time the volatility and liquidity factors. Different results are reported as to market timing abilities in Sherman et al. (2017) and Yi et al. (2019). While Yi et al. (2019) find insignificant market timing abilities in overall Chinese mutual funds, Sherman et al. (2017) detect some degree of market timing abilities. These studies use both TM and HM models.

The remainder of this article proceeds as follows. Section 1 presents the data used for Chinese mutual funds market timing analysis. Section 2 discusses TM, HM, and Kalman filter model. Section 3 applies these models to Chinese mutual funds data described in Section 1. Section 4 presents discussion of possible future research and conclusion of this article.

2. Data

Chinese stock and mutual fund data are collected from Wharton Research Data Services (WRDS, www.wharton.upenn.edu). Chinese common data are found in China Stock Market & Accounting Research (CSMAR) which includes company ID, market value, and monthly return. Mutual fund data are also found in China Stock Market & Accounting Research (CSMAR) which includes fund's ID, trading months, monthly average prices, and monthly returns. Chinese factors, excess market returns, small minus big (SMG), value minus growth (VMG) are obtained from Contributed Data.

I collect 904 Chinese mutual funds from Jul 2002 to Jun 2018 from the CSMAR data set. However, two criteria are applied to obtain sample data for the study of Chinese mutual funds' market timing abilities. Firstly, I focus only on actively managed mutual funds. Timing abilities are less meaningful when the fund managers use an investment strategy that simply tracks market index. Secondly, funds with insufficient period of time of observation are excluded from

sample data to produce more meaningful results. I choose the funds that have at least 36 months consecutive return data. These two criteria produce 141 sample funds from Jul 2002 to Jun 2018.

Table 1 shows the summary statistics of Chinese common stock return data.

3. Return-based factor timing models

The early models for evaluating the portfolio investment performance were built on the CAPM by Sharpe (1964) and Lintner (1965): A constant term is added to the standard CAPM to capture the superior performance of fund managers.

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + \varepsilon_{pt} \quad (1)$$

The term α_p represents the portion of portfolio excess return that is above or below what the portfolio is supposed to earn in the market. $\alpha_p > 0$ implies that the fund manager has superior forecasting abilities than other managers to generate more return.

However, Treynor and Mazuy (1966), Jensen (1968), Fama (1972), and Henriksson and Merton (1981) argue that managers' timing abilities can be divided into two parts: selection ability and timing ability. The former refers to the forecast abilities related to price movement of selected individual stocks, while the latter is the forecast abilities related to price movement of the stock market as a whole. Thus, it is important to model both abilities simultaneously. Otherwise, misjudgment of one ability may result in bias in the other and guide the managers in the wrong direction.

Most of the empirical studies of investment performance that attempts to separate these two abilities are based on the TM and HM models. This section shortly discusses two methods. Then I present the Kalman filter method

3.1. Treynor and Mazuy (TM) model

Treynor and Mazuy (1966) attempt to capture the market timing abilities by adding the quadratic excess market return term to the standard portfolio performance evaluation model (1):

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P(r_{m,t} - r_{f,t})^2 + \varepsilon_{P,t} \quad (2)$$

where γ_P represents the coefficient of market timing abilities of portfolio manager. The TM model argues that if the portfolio manager is able to time the market, then he will have greater exposure to the market factor when the excess market return is high. Similarly, he will have less exposure to the market factor when the excess market return is low. This implies that the relationship between portfolio return and market return is convex, which gives rise to the quadratic excess market return term in the TM model. The one-factor TM model (2) can be extended to the four-factor model:

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P(r_{m,t} - r_{f,t})^2 + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_{P,t} \quad (3)$$

3.2. Henriksson and Merton (HM) model

Henriksson and Merton (1981) develop an idea similar to the TM model, where they use a regression of the form:

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P \max(r_{m,t} - r_{f,t}, 0) + \varepsilon_{P,t} \quad (4)$$

Instead of the square term in the TM model, the HM model uses a max function to capture whether the fund managers can time the up/down markets. The four-factor HM model can be written as

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P \max(r_{m,t} - r_{f,t}, 0) + \beta_{SMB}SMB_t \quad (5)$$

$$+ \beta_{HML}HML_t + \varepsilon_{P,t}$$

3.3. Kalman filter model

This subsection develops the Kalman filter model to examine the mutual funds' market timing model. As in Mamaysky et al. (2008), I assume that there is a signal process that mutual funds use to trade their assets. This assumption provides two advantages over the previous two methods. Firstly, it allows the model to incorporate the dynamic nature of funds' alphas and betas. Individual alpha and beta are assumed to be time-constant but the portfolio alpha and beta become time-varying because fund managers dynamically adjust their portfolio weight according to the signal they receive at each time. Thus, it is possible to observe how the portfolio betas are correlated to the excess market returns over time. This provides more intuitive measure of market timing abilities than the measures devised by the TM and HM model. Secondly, the model does not require the exact portfolio holding information. Since Chinese mutual funds report their portfolio holdings only semiannually, it is difficult in practice to calculate monthly funds' portfolio beta by using the portfolio holdings. However, the introduction of a signal process here provides a way around this problem.

Suppose that a fund manager views the return on asset i as a linear factor model with constant alpha and factor loadings.

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it} \quad (6)$$

I assume that the fund's portfolio weights vary over time. This allows the model to have dynamic feature in funds' portfolio alpha and beta:

$$r_{Pt} - r_{ft} = w'_{t-1}(\alpha + \beta(r_{mt} - r_{ft}) + \varepsilon_t) = \alpha_{Pt} + \beta'_{Pt}(r_{mt} - r_{ft}) + \varepsilon_{Pt} \quad (7)$$

where

$$\begin{aligned}\alpha_{Pt} &= w'_{t-1}\alpha \\ \beta_{Pt} &= \beta w'_{t-1} \\ \varepsilon_{Pt} &= w'_{t-1}\varepsilon_t\end{aligned}\tag{8}$$

with w, α and ε , the I by 1 vectors containing elements w_i, α_i and ε_i . In a single factor model, β -term is a I by 1 vector but it becomes a I columns matrix in a multiple factor model.

Let F_t be some signal that the fund managers use to trade assets. Suppose that F_t follows the AR(1) process:

$$F_t = vF_{t-1} + \eta_t\tag{9}$$

where the v represents the extent to which the signal's value persists over time and η_t is assumed to be an independently and identically distributed innovation with $N(0, \sigma_\eta^2)$. The fund managers use this signal F_t to trade their assets at each time and the resulting portfolio weight dynamics is assumed to follow

$$w_{it} = \bar{w}_i + l_i F_t,\tag{10}$$

where $\bar{w}_i$ is the steady-state fraction of the trading strategy of a security i . The variable l_i represents the security i 's loading on a signal F_t . If the signal contains favorable information about security i at time t , the fund manager increases his portfolio weight on asset i at t . If the signal contains unfavorable information, he shifts his portfolio weight in the opposite direction. How much the portfolio weight changes depend on how heavily the security i loads on the signal. This formulation allows the dynamics of fund's portfolio alpha and beta as follows:

$$\begin{aligned}\alpha_{Pt} &= \bar{w}'\alpha + l'\alpha F_t = \bar{\alpha}_P + b_P F_{t-1} \\ \beta_{Pt} &= \beta \bar{w} + \beta l F_{t-1} = \bar{\beta}_P + c_P F_{t-1}\end{aligned}\tag{11}$$

This gives the following the funds' portfolio return dynamics:

$$r_{Pt} - r_{ft} = \bar{\alpha}_P + \bar{\beta}_P(r_{mt} - r_{ft}) + [b_P + c_P(r_{mt} - r_{ft})]F_{t-1} + \varepsilon_{Pt}\tag{12}$$

Equations (4) and (7) now form a state space model (SSM) which can be estimated by the standard linear Kalman filtering algorithm and maximum likelihood method.

Kalman filter algorithm

The Kalman filter is a recursive estimator that consists of two stages: prediction and update stages.

Prediction stage	
Predicted signal estimate	$\hat{F}_{t t-1} = v\hat{F}_{t-1 t-1}$
Predicted signal variance	$P_{t t-1} = v^2 P_{t-1 t-1} + \sigma_\eta^2$

The prediction stage uses the signal estimate from the previous update stage to predict the current signal. The variance P of signal $\hat{F}$ is predicted in a similar way.

Update stage	
Measurement pre-fit residual	$\tilde{y}_t = r_{Pt} - r_{ft} - (\bar{\alpha}_P + \bar{\beta}_P(r_{mt} - r_{ft}) + [b_P + c_P(r_{mt} - r_{ft})]\hat{F}_{t t-1})$
Pre-fit variance	$S_t = [b_P + c_P(r_{mt} - r_{ft})]^2 P_{t t-1} + \sigma_{\varepsilon_P}^2$
Kalman gain	$K_t = P_{t t-1}[b_P + c_P(r_{mt} - r_{ft})]S_t^{-1}$
Updated signal estimate	$\hat{F}_{t t} = \hat{F}_{t t-1} + K_t\tilde{y}_t$
Updated signal variance	$P_{t t} = (1 - K_t[b_P + c_P(r_{mt} - r_{ft})]) P_{t t-1}$
Measurement post-fit residual	$\tilde{y}_{t t} = r_{Pt} - r_{ft} - (\bar{\alpha}_P + \bar{\beta}_P(r_{mt} - r_{ft}) + [b_P + c_P(r_{mt} - r_{ft})]\hat{F}_{t t})$

The signal estimate produced in the prediction stage did not make use of information observed at t yet. The measurement pre-fit residual is the difference between the observed portfolio

return and the predicted portfolio return (where the prediction is made by $\hat{F}_{t|t-1}$). The variance of the measurement pre-fit residual is S_t . The update stage combines the signal estimate $\hat{F}_{t|t-1}$ in the prediction stage with the measurement pre-fit residual $\tilde{y}_t$ to produce better signal estimate, $\hat{F}_{t|t}$. The Kalman gain is the relative weight given to $\hat{F}_{t|t-1}$ and $\tilde{y}_t$ that leads to the usage of more accurate information. If the predicted signal variance $P_{t|t-1}$ is small relative to pre-fit variance S_t , then the Kalman gain puts more weight on $\hat{F}_{t|t-1}$ as it is more trustworthy than $\tilde{y}_t$. If S_t is small relative to $P_{t|t-1}$, then the Kalman gain puts more weight on the observed information, $\tilde{y}_t$. Consequently, the Kalman gain minimizes the updated signal variance $P_{t|t}$ which makes the error of the signal estimate as small as possible. Finally, the updated signal $\hat{F}_{t|t}$ generates the measurement post-fit residual $\tilde{y}_{t|t}$ and goes to the next prediction stage.

4. Empirical results

One way to assess the reliability of the models is to see the proportion of false positives generated. Statistical hypothesis can be over-rejected If a model yields false positives at too high rate. This section discusses which models in the previous section are suitable for explaining the market timing abilities of Chinese mutual fund managers.

To this end, I follow the framework of Mamaysky et al. (2008). The monthly data of Chinese stock return data is sorted into 4-years windows and size deciles with the assumption that the size deciles do not have the market timing abilities. Based on this assumption, a properly specified model should produce the proportion of false positives at the specified level of significance. For example, 10% significance level tests should provide four false positives among 40 deciles created by the double sorted data.

Table 2 shows the monthly market timing abilities of size deciles using the TM model. The

results from the one-factor (panel A) and four-factor (panel B) models show similar patterns, with significant timing coefficients concentrated in 2014-2018. At the 10% significance level, both one-factor and four-factor models contain a total of nine significant coefficient deciles, respectively, which is 22.5% of all portfolios. This implies that both one-factor and four-factor TM model may over-reject the hypothesis that tests market timing abilities.

Table 3 shows the monthly market timing abilities of size deciles using the HM model. As in the TM model, the one-factor (panel A) and four-factor (panel B) models have a similar pattern. However, the four-factor HM model produces less false positives than the one-factor HM model. Ten(25%) deciles under the one-factor HM model and seven(17.5%) under the four-factor HM model have significant timing coefficient at the 10% level. Despite significant improvement in the four-factor model, the percentage value is still larger than the corresponding 10%.

Table 4 shows the monthly market timing abilities of size deciles using the Kalman filter model. As in the two previous models, the one-factor (panel A) and four-factor (panel B) models have a similar pattern. However, the Kalman filter models produce less false positives than two models. Moreover, the proportion of the false positives generated by the four-factor Kalman filter model is close to their corresponding confidence level. 17.5% of all mutual funds under the one-factor Kalman filter model and 12.5% under the four-factor Kalman filter model have significant timing coefficient at the 10% level.

In sum, Table 2 – 4 apply the three models to the Chinese stock size deciles, where their monthly returns do not show the market timing abilities. Thus, well-specified models should not generate high rates of false positives. These tables do not provide any evidence on whether Chinese mutual funds time the market. Essentially, Table 2 – 4 examines the model's suitability for testing the timing abilities. Among the market timing models, the Kalman four-factor model has the lowest rate of false positives that is close to the corresponding significance level, 10%. Thus, the Kalman four-factor model expects to capture the market

timing abilities more reliably than other models when it is applied to the mutual fund return data.

Table 5 shows the aggregate market timing abilities of the Chinese mutual fund managers estimated by the four-factor TM, HM, and Kalman filter models. The three market timing models are applied to the monthly return data of equal-weighted Chinese mutual fund portfolios for four 4-years subperiods. The TM and HM models show similar patterns in the first two rows. Except the subperiod 2010-2014, all the subperiods exhibit negative market timing parameters. However, only the subperiod 2014-2018 has a significant result. Thus, the TM and HM models conclude that Chinese mutual fund managers are the market timers only in the subperiod 2014-2018. However, slightly different results are derived by the Kalman filter. While the subperiods 2002-2006 and 2010-2014 have positive timing parameters, they are not significant. On the other hand, the subperiods 2006-2010 and 2014-2018 have significantly negative timing parameters. Hence, the Kalman filter detects one more subperiod of significant aggregate timing behavior than the TM and HM models.

As discussed in Table 2 – 4, the four-factor Kalman model expects to produce more reliable results. Thus, the result of the significant timing behavior in both subperiods 2006-2010 and 2014-2018 is more reliable than the result of significant timing behavior only in the subperiod 2014-2018.

5. Discussion

This section discusses several issues that possibly add more explanatory power to the previous results.

5.1. Small number of samples

The previous results are driven by the actively managed Chinese mutual funds from WRDS.

The total number of the actively managed Chinese mutual funds is 141. The small number of samples can make the empirical results unreliable. Combining other Chinese data set such as RESSET financial research dataset (www.resset.cn) or WIND can add more explanatory power on the results.

5.2. Survivorship and incubation bias

Exclusion of the newly born funds during the sample period might alleviate the incubation bias problem. However, exclusion of these funds can generate statistically weaker results here as it makes small sample number even smaller.

One way to check the survivorship bias is to check whether all the funds were in operation until the end of the sample period. If all the funds were in operation until June 2018, the sample funds in this article are likely to be free of survivorship bias.

5.3. Dependency of alphas and betas on the same signal

The Kalman filter in this article models portfolio alphas and betas in a way that they depend on the same signal. This assumption may lead to spurious relation between the security selection skill and the market timing skill. Thus, as in the OLS-based models, the Kalman filter model here may also suffer from mis-specified model problem. Introduction of another signal process to handle alpha and beta separately may improve performance of estimating portfolio alphas and betas.

5.4 Investment objectives and other timing abilities

Assuming the Kalman filter model performs well, it would be interesting to examine whether the Kalman filter model coherently performs better with respect to other timing abilities such as, size timing, volatility timing, and liquidity timing. Yi et al. (2019) use the TM and HM models to show that Chinese mutual funds significantly time the volatility and liquidity factors. One may examine whether the volatility and liquidity timing factors are also captured by the Kaman

filter framework.

Yi et al. (2019) documents that there is no clue of the market timing abilities in overall Chinese mutual fund market. However, he found evidence on the market timing abilities among growth funds. Applying the Kalman filter to the funds with different investment style can be interesting future research.

6. Conclusion

The actively managed funds attempt to trade assets to generate a superior return than other fund managers. The mutual fund performance literature has focused on the two types of managers' skills: the security selection skill and the market timing skill. As incorrect assessment of one ability will lead to bias in the other ability, disentanglement of the two source of forecasting abilities is important.

This article uses the Kalman filter model developed by Mamaysky et al. (2008) to investigate whether the model reliably detects the market timing abilities of Chinese mutual fund managers. I compare the Kalman filter model to the widely used market timing models by Treynor and Mazuy (1966) and Henriksson and Merton (1981). The comparison of model performance is based on the rate of the false positives generated when the models are applied to Chinese stock size deciles. Among the three models, the (four-factor) Kalman filter model produces the least false positives and its rate is close to the corresponding confidence level. This implies that the Kalman filter model performs better in detecting the manager's timing skills. Based on this idea, the TM, HM, and Kalman models are applied to the monthly return data of Chinese mutual funds. While the TM and HM models detect the significant timing skills in the period 2014-2018, the four-factor Kalman filter captures the significant market timing behavior in Chinese mutual funds during the periods 2006-2010 and 2014-2018. Based on the false positive tests on the Chinese stock size deciles, the results from the four-factor

Kalman filter is more reliable.

There is room for improvement in this article. The empirical results are still subjective to many issues discussed in section 5. Further tests are necessary to give stronger support to the conclusion.

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Appendix

Table 1. Summary statistics of the data.

Variables	Mean	STD	Min	Max
Panel A. Summary of monthly return of Chinese factors				
R_f	0.0020359	0.000586417	0.0011000	0.0034000
$R_m - R_f$	0.0060562	0.0802876	-0.2547000	0.2458000
SMB	0.0080203	0.0469831	-0.1735000	0.1773000
VMG	0.0129333	0.0389613	-0.1028000	0.1517000
Panel B. Summary of monthly return of Chinese stock size deciles				
Decile 1	-0.0017296	0.0687813	-0.5005264	0.1754502
Decile 2	0.000931084	0.0748263	-0.5672232	0.1754502
Decile 3	0.0036515	0.0648844	-0.2791134	0.1586680
Decile 4	0.0047393	0.0754984	-0.4733736	0.1725736
Decile 5	0.0035638	0.0716234	-0.3454027	0.2301076
Decile 6	0.0019255	0.0723114	-0.3641992	0.1732364
Decile 7	0.0036419	0.0710544	-0.3355756	0.2593651
Decile 8	0.0062840	0.0678823	-0.1962425	0.2406007
Decile 9	0.0056287	0.0723075	-0.1943621	0.2307844
Decile 10	0.0074445	0.0666186	-0.1981195	0.2563385

Panel A summarizes the monthly Fama and French three factors. Panel B summarizes the average monthly returns for the size deciles of the Chinese stocks. The sample period is from July 2002 to June 2018.

Table 2. Monthly market-timing ability of the size decile: one-factor and four-factor TM models

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P(r_{m,t} - r_{f,t})^2 + \varepsilon_{P,t}$$

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P(r_{m,t} - r_{f,t})^2 + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_{P,t}$$

Periods	Decile									
	1	2	3	4	5	6	7	8	9	10
A. TM 1-factor timing parameters of the 10 EW size portfolios										
2002	-2.09031*	-0.73374	-0.32687	-1.72538	-0.31806	-0.52782	-2.00765	-1.92665	-1.42100	-2.18133*
2006	-0.06199	-0.42700	-1.33593*	-0.70331	-0.66015	-0.30084	-0.11743	-0.49056	0.09473	-1.00218
2010	0.12989	0.31913	-0.60338	-0.47439	-0.52843	-1.19978	-0.57598	-0.81678	-0.49476	0.34575
2014	-0.08078	-0.47849	-0.69888	-1.36166*	-1.58081*	-0.73744*	-0.89882*	0.51582*	-0.47563	-0.78389*
2002	(0.0636)	(0.5218)	(0.7794)	(0.1397)	(0.7624)	(0.6670)	(0.1622)	(0.1508)	(0.2832)	(0.0582)
2006	(0.8752)	(0.3621)	(0.0222)	(0.2393)	(0.3964)	(0.7005)	(0.8862)	(0.4181)	(0.9220)	(0.2757)
2010	(0.7475)	(0.6334)	(0.3620)	(0.4980)	(0.4619)	(0.1396)	(0.5770)	(0.2292)	(0.3864)	(0.5855)
2014	(0.8037)	(0.3414)	(0.1284)	(0.0040)	(0.0007)	(0.0408)	(0.0460)	(0.0918)	(0.2787)	(0.0780)
B. TM 4-factor timing parameters of the 10 EW size portfolios										
2002	-1.47268	-0.36095	0.36270	-0.92899	-0.06377	-0.03276	-1.67292	-1.70831	-1.37901	-2.24014*
2006	0.06273	-0.27148*	-1.11157*	-0.52163	-0.52756	-0.26784	-0.15110	-0.40751	0.09003	-0.92806
2010	0.23103	1.04982	0.23453	-0.06952	0.15284	-0.37611	0.58877	-0.29698	0.21775	0.93461
2014	-0.04693	-0.23268	-0.52734	-1.23449*	-1.35784*	-0.57403*	-0.69701*	0.51940*	-0.24048	-0.75945*
2002	(0.1996)	(0.7635)	(0.7636)	(0.4343)	(0.9544)	(0.9797)	(0.2645)	(0.2217)	(0.3195)	(0.0635)
2006	(0.8600)	(0.5399)	(0.0384)	(0.3713)	(0.5025)	(0.7347)	(0.8559)	(0.5061)	(0.9272)	(0.3279)
2010	(0.5775)	(0.0949)	(0.6866)	(0.9233)	(0.8263)	(0.6238)	(0.5383)	(0.6571)	(0.6664)	(0.1335)
2014	(0.8785)	(0.5665)	(0.1966)	(0.0065)	(0.0002)	(0.0563)	(0.0609)	(0.0990)	(0.4635)	(0.0915)

Within each 4-year window and size decile, the one-factor and four-factor TM models are applied to estimate funds' timing abilities from. The p-values are in parentheses. In both one-factor and four-factor TM model, 22.5% of the mutual fund portfolios has significant market timing coefficients at the 10% level.

Table 3. Monthly market-timing ability of the size decile: one-factor and four-factor HM models

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P \max(r_{m,t} - r_{f,t}, 0) + \varepsilon_{P,t}$$

$$r_{P,t} = \alpha_P + \beta_P(r_{m,t} - r_{f,t}) + \gamma_P \max(r_{m,t} - r_{f,t}, 0) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_{P,t}$$

Periods	Decile									
	1	2	3	4	5	6	7	8	9	10
A. HM 1-factor timing parameters of the 10 EW size portfolios										
2002	-0.68662*	-0.31793	-0.24492	-0.50277	-0.20304	-0.30570	-0.67197*	-0.58681*	-0.41474	-0.59074*
2006	-0.00480	-0.12487	-0.50206*	-0.29215	-0.17160	-0.05985	0.04147	-0.18203	0.18982	-0.38562
2010	0.02842	0.12662	-0.11945	-0.06896	-0.10684	-0.17170	-0.12822	-0.19965	-0.13104	0.06343
2014	-0.00455	-0.24478	-0.29242	-0.47355*	-0.58949*	-0.28345*	-0.33562*	0.18443	-0.12899	-0.31358*
2002	(0.0145)	(0.2700)	(0.4047)	(0.0873)	(0.4438)	(0.3220)	(0.0619)	(0.0817)	(0.2143)	(0.0418)
2006	(0.9804)	(0.5915)	(0.0865)	(0.3247)	(0.6571)	(0.8773)	(0.9187)	(0.5446)	(0.6916)	(0.3982)
2010	(0.7957)	(0.4860)	(0.5081)	(0.7177)	(0.5850)	(0.2206)	(0.6482)	(0.2807)	(0.3992)	(0.7133)
2014	(0.9725)	(0.2285)	(0.1163)	(0.0149)	(0.0021)	(0.0530)	(0.0671)	(0.1385)	(0.4703)	(0.0822)
B. HM 4-factor timing parameters of the 10 EW size portfolios										
2002	-0.56375*	-0.25207	-0.10754	-0.32659	-0.16218	-0.21490	-0.61921	-0.55483	-0.42010	-0.61435*
2006	-0.05709	-0.05709	-0.40141	-0.20996	-0.09307	-0.02642	0.04215	-0.13091	0.20703	-0.34892
2010	0.04320	0.32620	0.09984	0.03414	0.06902	-0.05387	0.17490	-0.05192	0.04973	0.20401
2014	-0.01177	-0.16366	-0.24427	-0.43317*	-0.52885*	-0.22912*	-0.27582*	0.18824	-0.05351	-0.31756*
2002	(0.0472)	(0.4003)	(0.7221)	(0.2713)	(0.5615)	(0.5044)	(0.0966)	(0.1113)	(0.2252)	(0.0416)
2006	(0.8063)	(0.7950)	(0.1357)	(0.4681)	(0.8116)	(0.9462)	(0.9185)	(0.6666)	(0.6709)	(0.4586)
2010	(0.7082)	(0.0541)	(0.5255)	(0.8615)	(0.7143)	(0.7956)	(0.4996)	(0.7747)	(0.7164)	(0.2289)
2014	(0.9247)	(0.3181)	(0.1390)	(0.0200)	(0.0003)	(0.0605)	(0.0676)	(0.1416)	(0.6881)	(0.0814)

Within each 4-year window and size decile, the one-factor and four-factor HM models are applied to estimate funds' timing abilities from. The p-values are in parentheses. 25% of all mutual funds under the one-factor HM model and 17.5% under the four-factor HM model have significant timing coefficient at the 10% level.

Table 4. Monthly market-timing ability of the size decile: one-factor and four-factor Kalman filter models

Periods	Decile									
	1	2	3	4	5	6	7	8	9	10
A. Kalman filter 1-factor timing parameters of the 10 EW size portfolios										
2002	-0.63391*	0.1342	0.1233	0.06673	-0.04016	0.18610	-0.16178	-0.15138	0.1513	-0.05348
2006	0.00075	0.14109	-0.36748*	-0.16748	0.07207	0.1207	0.13783	0.14799	-0.5638*	0.1465
2010	-0.02365	-0.16148	0.0156	0.03633	0.05783	0.0672	-0.11743	0.15781	-0.16008	-0.03148
2014	-0.083	-0.1043	0.0258	-0.26748*	-0.54458*	-0.60458*	-0.57391*	0.1825	-0.1134	-0.02365
2002	(<.0001)	(0.2314)	(0.2415)	(0.7654)	(0.7964)	(0.7784)	(0.2761)	(0.2961)	(0.2883)	(0.3024)
2006	0.9959	(0.2288)	(<.0001)	(0.2661)	0.6264	(0.2715)	(0.3561)	(0.2855)	(<.0001)	(0.2991)
2010	0.8732	(0.2729)	(0.9074)	0.8064	(0.7024)	(0.6324)	(0.3963)	(0.2961)	(0.2681)	(0.3529)
2014	(0.3516)	(0.2517)	(0.8534)	(-0.0661)	(<.0001)	(<.0001)	(<.0001)	(0.2140)	(0.2413)	(0.3716)
B. Kalman filter 4-factor timing parameters of the 10 EW size portfolios										
2002	-0.44347*	-0.13741	-0.18278	0.09605	0.14553	-0.04016	-0.03786	0.23042	0.20021	-0.14388
2006	-0.05465	-0.16759	-0.03878	0.02447	-0.21325	-0.21053	-0.21114	0.18228	-0.10144	-0.18511
2010	0.05785	0.11476	0.16816	0.05252	-0.27172*	-0.12826	-0.21742	0.06629	-0.09486	-0.16511
2014	0.11744	-0.04951	-0.08624	-0.15293	-0.24892*	-0.37066*	-0.27963*	0.17489	-0.19327	0.18610
2002	(0.0016)	(0.3517)	(0.2137)	(0.5161)	(0.3237)	(0.7864)	(0.7983)	(0.1151)	(0.1724)	(0.3292)
2006	(0.7031)	(0.3817)	(0.7935)	(0.8688)	(0.1456)	(0.1509)	(0.1390)	(0.2150)	(0.4927)	(0.2078)
2010	(0.6961)	(0.4373)	(0.3573)	(0.7229)	(0.0617)	(0.4508)	(0.1377)	(0.6544)	(0.5213)	(0.2742)
2014	(0.4266)	(0.7382)	(0.5600)	(0.2994)	(0.0880)	(0.0095)	(0.0542)	(0.2686)	(0.1881)	(0.1487)

Within each 4-year window and size decile, the one-factor and four-factor Kalman filter models are applied to estimate a beta time series. The market timing skills parameter is defined as the correlation between the time series of portfolio beta and the market return. The p-values are in parentheses. 17.5% of all mutual funds under the one-factor Kalman filter model and 12.5% under the four-factor Kalman filter model have significant timing coefficient at the 10% level.

Table 5. Market timing abilities of Chinese mutual funds during 2002-2018

Models	Periods			
	2002-2006	2006-2010	2010-2014	2014-2018
TM	-0.94968 (0.4041)	-0.40340 (0.4872)	0.26667 (0.5816)	-0.51509* (0.0275)
HM	-0.38355 (0.1761)	-0.09754 (0.7350)	0.08942 (0.4948)	-0.20695* (0.0290)
Kalman filter model	0.19939 (0.1742)	-0.44136* (0.0017)	0.15189 (0.3027)	-0.34204* (0.0173)

The table displays the market timing parameters obtained from the four-factor TM, HM, and Kalman filter models in each 4-years window. P-values are in parenthesis. While the TM and HM models identify only the period 2014-2018 as a significant market timing period, the period 2006-2010 is additionally captured by the Kalman filter model.