Pacific-Basin Finance Journal 44 (2017) 80–96

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Mutual fund managers' timing abilities

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ARTICLE INFO

JEL classifications:
G10
G11
G19
G29

Keywords:
Market timing
Liquidity timing
Volatility timing

ABSTRACT

This paper examines Chinese mutual fund managers' abilities to time market, market volatility, and market-wide liquidity. Using a sample of Chinese mutual funds, we employ both cross-sectional and bootstrap analyses and find strong evidence that, during 2001–2011, Chinese mutual fund managers demonstrated the ability to time market returns, volatility, and market liquidity. We also find top timers outperform bottom timers by 6–7% annually in out-of-sample tests, manifesting the practical meaning of timing ability. We then conduct robustness checks of our findings and the results are the same.

1. Introduction

There has been a lasting debate regarding whether mutual fund managers can successfully time several market condition dimensions. One strand of the literature focuses on managers' ability to time market returns but does not reach a consistent conclusion. For example, Treynor and Mazuy (1966) construct a model to test if managers can outguess the market but find no evidence to support their assumption. Henriksson and Merton (1981) derive both non-parametric and parametric models and do not support the market-timing hypothesis. However, Bollen and Busse (2001) find mutual funds exhibit significant timing ability, based on daily returns. Another group of studies (e.g. Busse, 1999; Giambona and Golec, 2009; Kim and In, 2012) investigate whether mutual fund managers increase market exposure when predicting a decrease in volatility and report mostly positive findings. In addition, liquidity-timing ability is a new valid perspective with regard to the timing issue. Cao et al. (2013b) show that mutual fund managers can time market liquidity and their timing ability can predict future fund performance. In sum, most studies are largely based on developed economies and have obtained mixed results. However, a scant literature examines mutual fund managers' timing ability from a more comprehensive perspective in major emerging economies such as China, the second largest and most influential economy. In this paper, we focus on several dimensions of timing ability, including the return timing, volatility timing, and liquidity timing of Chinese mutual funds, and further ask whether timing ability can provide economic value to investors.

Recently, some researchers give more insights into funds' timing behavior in depth and provide improvement. The challenge of examining mutual fund performance is to distinguish skill from luck. Because many may experience superior performance by chance given the multitude of funds (Fama and French, 2010). Some papers use a cross-sectional bootstrap analysis as an effective way to distinguish between 'skill' and 'luck' for individual funds (e.g., Kosowski et al., 2006; Cuthbertson et al., 2008; and Fama and French,

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[1] The author acknowledges research grants from National Natural Science Foundation of China (71673318, 71602198), the Program for Innovation Research and the Program for Excellent Academic Talent of the Central University of Finance and Economics.
[2] The author acknowledges the funding support from the National Natural Science Foundation of China (71232003 and 71573147).

http://dx.doi.org/10.1016/j.pacfin.2017.06.003
Received 19 January 2017; Received in revised form 5 April 2017; Accepted 3 June 2017
Available online 07 June 2017
0927-538X/

2010). Therefore, we apply the bootstrap method to study whether Chinese stock mutual funds have true timing skills rather than good luck. Kacperczyk et al. (2014) suggest that some of mutual fund managers have time-varying skills and they are able to successfully time the market only in recessions. We thus remove the sample in the crisis period from the main sample hereafter to conduct the robustness check in this paper. Ferson and Mo (2016) document that funds with superior ability are more likely to engage in adverse volatility timing behavior; that is, managers tend to increase market exposure when the volatility is high due to their option-like compensation. Yet very little research has been carried out to investigate whether Chinese mutual fund managers can time the market and whether the evidence derived from the developed economies could be consistent with the Chinese market. This paper fills a gap in the literature by providing a comprehensive study on Chinese mutual fund managers' timing abilities.

Chinese mutual funds have experienced dramatic growth in recent years and thus received a great deal of attention. There were only three equity-linked mutual funds managing $11.90 billion Chinese yuan at the end of 2001. At the beginning of the 21st century, the Chinese government implemented a strategic reform to cultivate mutual funds. After that, along with rapid growth of the Chinese stock market, the mutual fund industry became one of the fastest-growing industries in China. By the end of 2016, the total assets of equity-linked mutual funds (excluding index funds) grew to around $2.9 trillion Chinese yuan, accounting for 4.27% of GDP.[3] As the Chinese capital market is becoming more and more open, China has been presenting an increasing degree of integration with the global capital market during the last few years, especially after China's admission into the World Trade Organization and introduction of the Qualified Foreign Institutional Investor scheme. The characteristics of Chinese mutual fund managers are of keen interest to foreign investors. Thus, it is imperative for researchers to provide a deeper understanding of Chinese mutual fund industry. The purpose of this study is to help the understanding of Chinese mutual fund by providing a systematic analysis on the Chinese mutual fund timing abilities.

Why is it interesting to examine timing in the Chinese market? We conjecture that the timing abilities of Chinese mutual funds are different from those in other countries because Chinese mutual fund markets differ from other markets in several important ways.

The first is the dominance of individual investors and their speculative trading behaviors in China. The portion of institutional investors, including sophisticated and informed investors (e.g., Chinese mutual funds), accounted for < 15% of Shanghai and Shenzhen stock market shares at the end of 2012,[4] while the portion was > 60% in the U.S. market (Blume and Keim, 2012). Sophisticated institutional investors invest with less behavioral biases compared to individual investors. The irrational preferences and investment features of individual investors cause the predictability of Chinese stock market (Yi and He, 2016), suggesting the potential existence of timing abilities of Chinese mutual fund managers.

Second, compared with advanced economies, the information asymmetry issue is more severe in Chinese market, which is the second highest market based on stock price synchronicity among 40 markets internationally (Morck et al., 2000). This implies that the benefits reaped from collecting and processing such information would be very high for the capable investors (Chan and Hameed, 2006). Relative to individual investors, institutional investors, especially mutual funds, possess superior information discovering abilities (Liao et al., 2011). Thus, Chinese mutual fund managers have a greater information advantage to forecast trends of the macroeconomic factors and adjust their portfolio exposures.

Third, the Chinese market experiences frequent and large fluctuations relative to developed markets like the US. For example, the Chinese market appears a monthly stock market volatility reaching 9.65% while 4.45% on the S & P 500 between 1996 and 2015 (Chen et al., 2016). Higher volatility provides mutual fund managers more incentives to time the market, volatility, and liquidity. The reason is that the timing behavior is less rewarded in a less volatile market, resulting in that the manager may appear to be unskilled for reasons unrelated to her actual skills. In a later section, we show that timing behaviors are indeed rewarding in the Chinese market. Therefore, Chinese mutual funds provide an environment for examining if their managers are capable of timing the volatile market. In addition, Chinese mutual fund data does not suffer from survivorship bias because the mutual fund industry has experienced strong growth in the past two decades and few funds cease operation during the sample period.

There are several studies on Chinese mutual fund performance; however, the timing literature is still nascent for Chinese market. According to Tang et al. (2012), from 2004 to the first half of 2010, the average performance measures (the capital asset pricing model's alpha, the Fama–French (1993) alpha, and style benchmark-adjusted returns) of Chinese mutual funds were almost all positive, indicating that Chinese mutual funds outperform the market quite well. Li and Lin (2011) use Fama and French (1993) three-factor model and find that Chinese mutual funds can outperform the stock market benchmarks. Lin et al. (2013) show that Chinese mutual funds investment decisions are significantly affected by economic and political factors. About mutual fund timing, Chen et al. (2017) document that Chinese fund managers with a macro analyst background can time the market successfully because of their superior ability in forecasting government policy and macroeconomic trends. One closely related study is Yi and He (2016). They adopt the false discovery rate (FDR) to estimate the daily style timing ability of actively managed Chinese stock mutual funds and find positive evidence of mutual funds' market timing ability and its persistence. Our research, however, takes a different angle. Yi and He (2016) typically focus on the investment style of mutual funds, but do not investigate other important perspectives of timing as volatility and liquidity. In our paper, we use bootstrap methods to examine that in addition to market timing, Chinese mutual fund managers have other aspects of timing abilities.

We use 280 equity-oriented and mixed mutual funds during 2001–2011 and conduct the following analyses to test the timing ability of Chinese mutual fund managers. We construct timing models based on a traditional framework to explore the market exposure of mutual fund managers in relation to market conditions, including market returns, volatility, and liquidity. Specifically,

[3] Data source: WIND Database.
[4] Data source: WIND Database.

Table 1
Summary statistics.
This table presents data summary statistics. The returns of mutual funds (in percent per month) summarize the monthly returns on equity-oriented and mixed mutual funds and N is the number of funds that exist any time during the sample period. The other variables summarized in the table include stock market index excess returns (MKT), the market volatility measure (volatility), the Pástor–Stambaugh market liquidity measure (Pástor–Stambaugh liquidity), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (Momentum). Pástor–Stambaugh liquidity is the average liquidity cost (price impact) in percent for a 7 million yuan trade in 1996. The sample period is from 2001 to 2011.

	N	Mean	Median	STD	25%	75%
Return of mutual funds	280	1.064	1.104	0.860	0.651	1.433
MKT	132	0.498	0.639	9.004	− 5.509	5.093
Volatility	132	1.606	1.362	0.745	1.100	1.896
Pástor–Stambaugh liquidity	132	− 3.542	− 2.670	3.879	− 5.434	− 1.476
SMB	132	0.598	0.418	4.306	− 1.965	3.253
HML	132	0.154	0.340	3.850	− 1.499	2.410
Momentum	132	− 0.870	− 0.576	4.615	− 3.646	2.102

we estimate regression models to assess how a fund's beta in month $t-1$ changes with market conditions realized in month t, while exposure to other factors of the fund is controlled for. Our results document significant and positive timing abilities at the individual fund level by demonstrating that fund managers adjust market exposure based on their latest observations, including market returns, volatility, and liquidity. Thus, these findings indicate that the timing ability of Chinese mutual fund managers is not the same as that of mutual fund managers in developed economies.

We use the bootstrap method of Kosowski et al. (2006) and Jiang et al. (2007) to also test whether the significance of the timing ability is driven by luck. Specifically, we construct hypothetical funds that share similar risk exposure as actual funds but do not have timing ability and then compare the actual timing coefficient estimates with the corresponding distribution of estimates from the pseudo-funds. We further calculate out-of-sample alphas to verify that the timing skill of mutual funds can provide economic value for investors. We find top timers outperform bottom timers by 6–7% annually in out-of-sample tests. In addition, we conduct robustness tests to eliminate the impact of potential biases on our primary results about timing ability. For example, we solve the time-series correlation of timing measures, control for the influence of bond returns, exclude the financial crisis period, and examine the correlations between the three types of timing skills. Finally, we investigate the relation between investment styles and timing abilities and find that there are no significant differences in timing ability across the three investment-style categories of funds.

The remainder of the paper proceeds as follows: Section 2 describes the mutual fund data and methodology that we use to evaluate timing ability. Section 3 presents the cross-sectional and bootstrap analyses of mutual fund timing abilities and the economic value of timing skills by examining out-of-sample alphas for portfolios of funds at different levels of timing skills. Section 4 contains further analysis and discussions. Finally, Section 5 concludes the paper.

2. Data and methodology

2.1. Chinese mutual funds

Our mutual fund data are from the China Stock Market & Accounting Research (CSMAR) database, which belongs to GTA Education Tech Ltd., a leading Chinese financial data provider. We include only equity-oriented and mixed funds (excluding index funds) that invest only in the Chinese market and have existed for > 36 months between 2001 and 2011. Our sample thus includes 280 mutual funds.

Table 1 reports the summary statistics of our Chinese mutual fund sample. Over the sample period, the average monthly excess return of Chinese mutual funds is 1.06% (about 12.77% per year), with a standard deviation of 0.86%. The Chinese stock market averaged a monthly excess return (MKT) of 0.50%, with a standard deviation of 9.00%, from 2001 to 2011. Volatility, which is 1.61% per month, on average, is the market-wide volatility. Table 1 also shows the summary statistics of monthly Pástor–Stambaugh liquidity measures, which is − 3.54%, on average. Following Chen et al. (2017), the monthly data on these four risk factors that we use in this paper comes from China Asset Management Academy (CAMA),[5] which provides a detailed construction method and reliable calculation of the Carhart factors (SMB, HML, and MOM). These key variables are defined in the following.

Fig. 1 plots the time series of monthly Chinese market volatility from January 2001 to December 2011. The highest market volatility occurred throughout all of 2008 and the lowest occurred between 2003 and 2006. Fig. 2 plots the time series of monthly Pástor–Stambaugh market liquidity over the sample period. Pástor–Stambaugh market liquidity peaked at 0.16 in September 2008 and dropped to − 0.19 in October 2011. These extreme points are consistent with the date of the financial crisis; the volatility and liquidity of the Chinese A-share stock market that we use are therefore appropriate.

[5] http://sf.cufe.edu.cn/kxyj/kyjg/zgzcglyjzx/index.htm.

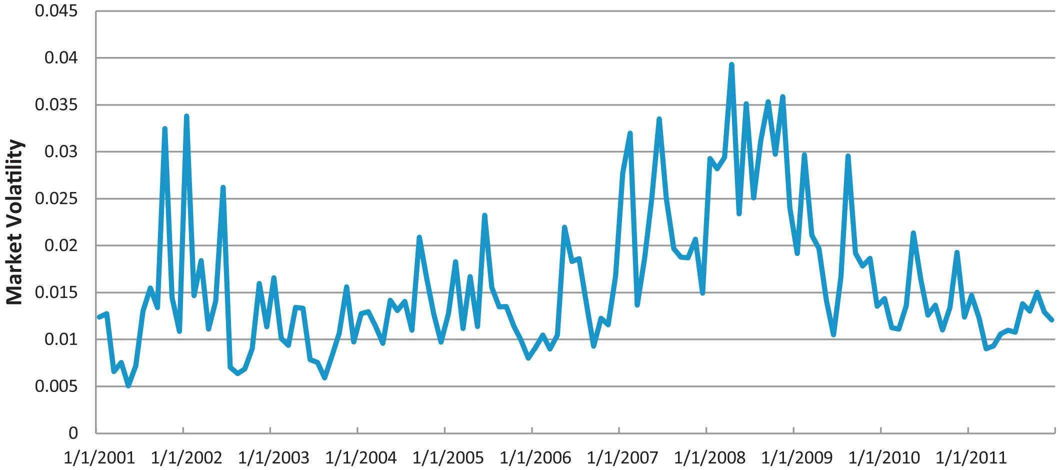

Fig. 1. Time series of monthly market volatility.
This figure plots the time series of the monthly market volatility measure. The sample period is from January 2001 to December 2011.

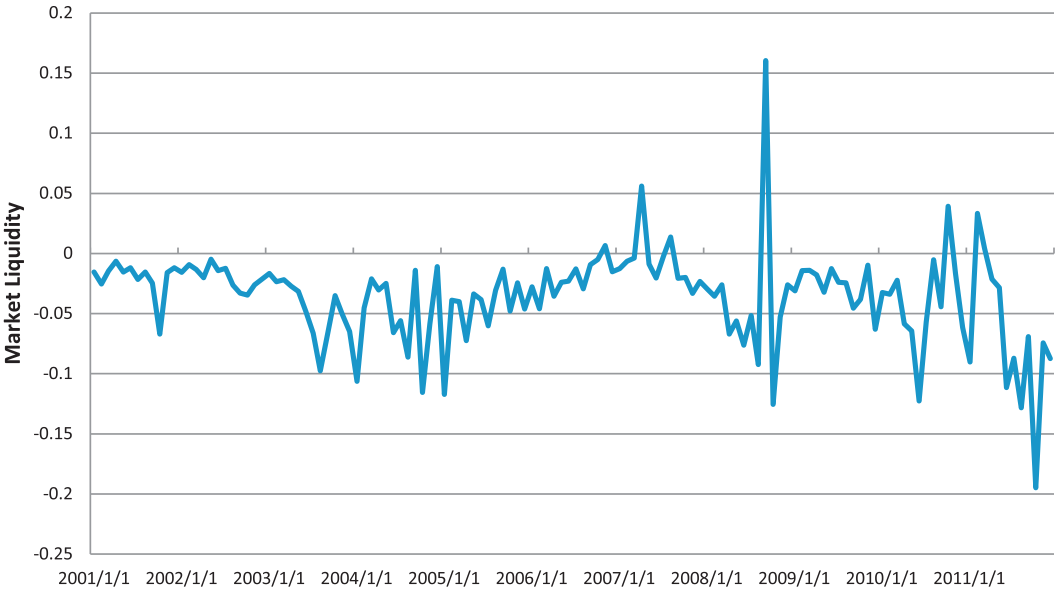

Fig. 2. Time series of monthly market liquidity.
This figure plots the time series of the monthly market liquidity measure developed by Pástor and Stambaugh (2003). The sample period is from January 2001 to December 2011.

2.2. Methodology

In this section, we describe the timing models in the following empirical work. We investigate the timing abilities of Chinese fund managers based on Carhart's (1997) four-factor model:

$$r_{p,t} = \alpha_p + \beta_{p,t-1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t} \tag{1}$$

where $r_{p,t}$ is the monthly return on fund p in excess of the risk-free return in month t; the risk-free return is the monthly return of a one-year Chinese deposit; MKT_t is the monthly return of outstanding value-weighted A-share Chinese stocks in excess of the risk-free rate in month t; and SMB_t, HML_t, and MOM_t are the month-t returns on the factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns, respectively.

In Eq. (1), to account for timing, we allow the market beta to be time-varying and denote it by $\beta_{p,t-1}$. The reason why the fund beta $\beta_{p,t-1}$ is expressed at time $t-1$ is that the manager generates it in month $t-1$ based on his forecast about market conditions in month t. Specifically, according to the literature on timing models (e.g., Admati et al., 1986; Ferson and Schadt, 1996), the market beta of fund p, denoted $\beta_{p,t-1}$, is a linear function of the fund manager's forecast of market conditions in excess of its time series average. Thus, we derive the specification.

$$\beta_{p,t-1} = \beta_{p,1} + \gamma_p E(market\ condition_t \mid I_{t-1}), \tag{2}$$

where I_{t-1} is the available information for fund managers in month $t-1$, $\beta_{p,1}$ measures fund p's average market beta, and γ_p reflects managers' timing skill, representing how the market beta of fund p changes with forecasts of market conditions. Eq. (2) presents different expressions for different dimensions of market conditions. As an example, when we focus on market returns, $\beta_{p,t-1} = \beta_{p,1} + \gamma_p(MKT_t + \upsilon_t)$, where υ_t is a forecast noise unknown until t. A positive γ_p means that fund p has a high (low) market beta under good (poor) market conditions. By inserting different timing models of Eq. (2) into Eq. (1), we construct the timing models (Eqs. 3 to 6) to examine the three timing skills based on managers' forecasts of market returns, market volatility, and market liquidity, respectively.

2.2.1. Market-timing models

We use the Treynor–Mazuy (1966) market-timing model and the Henriksson–Merton (1981) timing model to test whether Chinese mutual fund managers have market-timing ability, as follows, respectively:

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

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t}, \tag{4}$$

where MKT_t^2 is the square of the monthly market excess return in month t and Max(MKT_t, 0) equals the monthly market excess return in month t when it is positive and zero otherwise. The estimated coefficient γ_p reflects market-timing skill. A positive γ_p implies the existence of market-timing skill due to the successful adjustment of portfolio exposures prior to market advances or declines.

2.2.2. Volatility-timing model

We employ the following regression to test volatility-timing skill:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((V_{m,t} - \overline{V_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t}, \tag{5}$$

where γ_p represents volatility-timing ability and $V_{m,t}$ is the market volatility-timing measure in month t. For each day n, we calculate the outstanding value-weighted daily return of all A-share Chinese stocks using the firms' market value on trading day $n-1$ as weights in excess of the risk-free rate and we then calculate the monthly standard deviation of the daily market return to obtain $V_{m,t}$, where V_m is the average market volatility across all months in the sample. We subtract $\overline{V_m}$ from $V_{m,t}$ to remove the inference of forecast noise.

2.2.3. Liquidity-timing model

We use a methodology similar to that above and define the coefficient γ_p from the following regression as liquidity-timing ability:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((L_{m,t} - \overline{L_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t}, \tag{6}$$

where $L_{m,t}$ is the Pástor–Stambaugh (2003) liquidity measure in month t and $\overline{L_m}$ is the time-series mean of market liquidity measures across all months in the sample.

To calculate $L_{m,t}$, we select all A-share stocks in the Chinese market from January 1996 to December 2011. We eliminate all stocks with a closing price over 1000 yuan or under 2 yuan in any day during this period. Stocks with an observation period of < 15 days in any given month are dropped as well. For each A-share Chinese stock i in each month t, its liquidity measure $L_{m,t}$ in month t is obtained from the following regression:

$$\begin{aligned} r^e_{i,d+1,t} &= \theta_{i,t} + \phi_{i,t} r_{i,d,t} + L_{i,t}\, sign(r^e_{i,d,t}) * \nu_{i,d,t} + \varepsilon_{i,d+1,t}, \\ d &= 1, \ldots, D_{i,t}, \end{aligned} \tag{7}$$

where $r_{i,d,t}$ is the daily return of stock i on day d in month t; $r_{i,d,t}{}^e$ is the daily return of stock i in excess of the market return on day d in month t; $\nu_{i,d,t}$ is the volume (in yuan) for stock i on day d in month t, standardized by the average daily trading volume (7 million yuan) of A-share Chinese stocks in 2006; and $D_{i,t}$ is the number of trading days in month t. Controlling for lagged excess stock returns, $L_{i,t}$ measures the expected return reversal for a given volume and is expected to be negative and greater in magnitude if stock i is less liquid. The market liquidity measure in month t is then calculated as the average liquidity measure across individual stocks:

$$L_{m,t} = (m_{t-1}/m_1)^* \left(\sum_{i=1}^{N_t} L_{i,t}\right) \Big/ N_t, \tag{8}$$

where N_t is the number of stocks available in month t. Since the size of the equity market increases over time, the liquidity measure is scaled by market size at the beginning of the daily sample in the CSMAR database, where m_{t-1} is the total market value of all sample stocks at the end of month $t-1$, with month 1 referring to January 1996.

3. Empirical analysis

In this section, we examine whether mutual fund managers time the market, volatility, and liquidity by the cross-sectional distribution of t-statistics for the timing coefficients of each mutual fund and reveal the baseline findings. Then, we employ a bootstrap analysis to test the significance of the baseline result. We further demonstrate that Chinese mutual fund managers' timing

Table 2
Cross-sectional distribution of t-statistics for the timing coefficients across individual funds.

This table summarizes the distribution of t-statistics for the timing coefficients. For each fund with at least 36 monthly return observations, we estimate the Treynor–Mazuy market-timing model,

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

the Henriksson–Merton market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t};$$

the volatility-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(V_{m,t} - \overline{V_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t};$$

and the liquidity-timing model,

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

where $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include the market excess return (MKT), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (MOM). The term MKT_t^2 is the square of the monthly market excess return in month t, $V_{m,t}$ is the market volatility-timing measure in month t, $\overline{V_m}$ is the mean of market volatility, $L_{m,t}$ is the market liquidity measure in month t, and $\overline{L_m}$ is the mean of market liquidity. The coefficient γ_p measures the market-timing ability, the volatility-timing ability, and the liquidity-timing ability in the three models, respectively. The table reports the percentage of funds for which the t-statistics of the timing coefficient exceed the indicated values.

	Percentage of funds					
	$t \le -2.326$	$t \le -1.960$	$t \le -1.645$	$t \ge 1.645$	$t \ge 1.960$	$t \ge 2.326$
Market timing, Treynor	1.07	1.07	1.43	35.71	28.57	22.14
Market timing, Henriksson	0.00	1.43	2.50	40.00	33.57	24.29
Volatility timing	16.43	23.93	31.43	2.86	2.14	1.43
Liquidity timing	0.36	0.71	1.07	28.93	22.50	16.43

skill can indeed add economic value for investors.

3.1. Cross-sectional distribution of the t-statistics of timing abilities

We test market timing, volatility timing, and liquidity timing for individual funds using Eqs. (3) to (6), respectively. Table 2 reports the cross-sectional distribution of t-statistics for timing measures across individual funds. We observe the percentage of t-statistics greater than the indicated cutoff values. For example, the percentages of Chinese mutual funds that have t-statistics of the Treynor–Mazuy market-timing, Henriksson-Merton market-timing, and liquidity-timing measures > 1.645 are around 35.7%, 40.0%, and 28.9%, respectively. This result shows that the right tails of the whole sample are thicker than the left tails. Volatility-timing measures display the opposite trend, with 31.4% of sample funds lower than − 1.645. The distribution of t-statistics suggests that all three types of timing abilities significantly exist in Chinese equity-oriented and mixed mutual funds.

However, some funds might have significant t-statistics due to chance. In other words, when the sample is large, some funds can appear to exhibit significant timing ability even though in actuality no funds have timing ability. In addition, if funds invest with a similar strategy, their performance will display a similar pattern, which means their timing measures are dependent. Thus, the cross-sectional evidence is not sufficient to demonstrate the existence of Chinese mutual fund timing ability. In the next section, we use a bootstrap method to estimate if timing coefficients reflect true timing skills or are due to pure luck.

3.2. Bootstrap tests

Following the methodology of Kosowski et al. (2006) and Jiang et al. (2007), we use a bootstrap analysis to derive statistical inferences for three timing measures at the individual fund level. The main procedure of the bootstrap analysis is the random resampling and construction of a group of hypothetical funds with the same factor loadings as the original sample but devoid of any timing ability. Then we compare the timing coefficients between the actual and hypothetical funds.

Using the Treynor–Mazuy market-timing measure as an example, we first estimate the timing model in Eq. (3) for each fund p and retain the parameter estimates $\{\alpha_p, \gamma_p, \beta_{p,1}, \beta_{p,2}, \beta_{p,3}, \beta_{p,4}\}$, as well as a time series of residuals $\{\varepsilon_{p,t}\}$. We then randomly resample the residuals and generate a time series of bootstrapped residuals $\{\varepsilon_{p,t}{}^b\}$, where b is an index for the bootstrap iteration ($b = 1, 2, \cdots, B$). Next, we construct a pseudo-fund with no timing skills (i.e., $\gamma_p = 0$) and generate a time series of bootstrapped returns, $\{r_{p,t}{}^b\}$, as follows:

$$r_{p,t}^b = \alpha_p + \beta_{p,1}MKT_t + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t}^b. \quad (9)$$

Table 3
Bootstrap analyses of market, volatility, and liquidity timing.

This table presents the results of the bootstrap analysis of market timing, volatility timing, and liquidity timing. For each fund with at least 36 monthly return observations, we estimate the Treynor–Mazuy market-timing model,

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

the Henriksson–Merton market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t};$$

the volatility-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(V_{m,t} - \overline{V_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \varepsilon_{p,t};$$

and the liquidity-timing model,

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

where $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include the market excess return (MKT), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (MOM). The term MKT_t^2 is the square of the monthly market excess return in month t, $V_{m,t}$ is the market volatility-timing measure in month t, $\overline{V_m}$ is the mean of market volatility, $L_{m,t}$ is the market liquidity measure in month t, and $\overline{L_m}$ is the mean of market liquidity. The coefficient γ_p measures liquidity-timing ability. The first row reports the sorted t-statistics of the timing coefficients across individual funds for each timing ability and the second row shows the empirical p-values from the bootstrap simulations. The number of resampling iterations is 1000.

		Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
		1%	3%	5%	10%	10%	5%	3%	1%
Market timing	t-Stat	− 2.36	− 1.43	− 1.09	− 0.75	3.51	4.21	4.66	6.40
Treynor model	p-Value	0.56	0.99	1.00	1.00	0.00	0.00	0.00	0.00
Market timing	t-Stat	− 2.14	− 1.11	− 0.84	− 0.47	3.40	4.02	4.36	5.30
Henriksson model	p-Value	0.77	1.00	1.00	1.00	0.00	0.00	0.00	0.00
Volatility timing	t-Stat	− 4.23	− 3.64	− 3.23	− 2.77	0.63	1.20	1.58	2.65
	p-Value	0.02	0.00	0.00	0.00	1.00	1.00	0.98	0.25
Liquidity timing	t-Stat	− 1.74	− 1.37	− 1.22	− 0.99	3.02	3.68	4.12	4.45
	p-Value	1.00	1.00	1.00	1.00	0.00	0.00	0.00	0.03

We estimate the Treynor–Mazuy market-timing model (3) by using the pseudo-fund returns $\{r_{p,t}{}^{b}\}$ from the above steps. By construction, the bootstrapped market-timing estimate should be zero. Therefore, any non-zero bootstrapped market-timing estimate $\{\hat{\gamma}_p^b\}$ and its t-statistic $\{\hat{t}_{\hat{\gamma}_p}^b\}$ are purely due to sampling variation.

We repeat this process for all funds and obtain the cross-sectional statistics of the bootstrapped market-timing measures. We repeat the above steps for 1000 iterations to generate the empirical distribution of t-statistics for the pseudo-funds. Finally, we compare the values of the bootstrapped cross-sectional statistic (e.g., the top 10th percentile) from the iterations with the actual values of the cross-sectional statistics in the previous section and then determine whether the market-timing estimate can be explained by random sampling variation. If a large portion of the values of the bootstrapped cross-sectional statistics (e.g., the top 10th percentile) are greater than the value of the prior cross-sectional statistic, then our results in Table 2 are doubtful.

We also perform the above analysis on the Henriksson–Merton market-timing measure, volatility-timing measure, and liquidity-timing measure, respectively. Table 3 reports the top and bottom percentiles (1% to 10%) of the t-statistics and their p-values of the timing measures across individual Chinese funds from the bootstrap analysis. The results suggest that the top 1%, 3%, 5%, and 10% of Chinese mutual funds have a Treynor–Mazuy market-timing measure $t_{\hat{\gamma}}$ of 6.40, 4.66, 4.21, and 3.51, respectively, with empirical p-values all close to zero. Similar results hold for the Henriksson–Merton market-timing measure and liquidity-timing measure, which have $t_{\hat{\gamma}}$ values of 3.40 and 3.02 for the top 10% of Chinese mutual funds, respectively. Different from other timing measures, mutual fund market betas respond negatively to market volatility according to Busse (1999). Table 3 shows that the volatility-timing measure is significant and negative, that is, has a $t_{\hat{\gamma}}$ of − 2.77 for the bottom 10%, with an empirical p-value close to zero. For at least 10% mutual funds, there exists a strong negative relation between funds' market exposure levels and market volatility. This finding suggests that when the market volatility is higher than average, mutual fund managers reduce their exposure to the market and decrease the fund systematic risk level, consistent with Busse's (1999) work. To summarize, we can conclude that the top-ranked timing coefficients, including return timing, volatility timing, and liquidity timing, are not due to luck. In other words, we confirm the existence of all three timing abilities for top-ranked Chinese mutual fund managers.

Fig. 3.1 plots the kernel density distribution of the bootstrapped 10th percentile t-statistics of the Treynor–Mazuy market-timing measure, the Henriksson–Merton market-timing measure, the volatility-timing measure, and the liquidity-timing measure, respectively. The vertical lines show the actual t-statistics of the timing measures for the sample funds. These graphs indicate that the distribution of bootstrapped t-statistics is non-normal, unlike the conventional significance level under the normality assumption. Figs. 3.2 and 3.3 also plot the kernel density distribution of the bootstrapped fifth and first percentile t-statistics of the timing

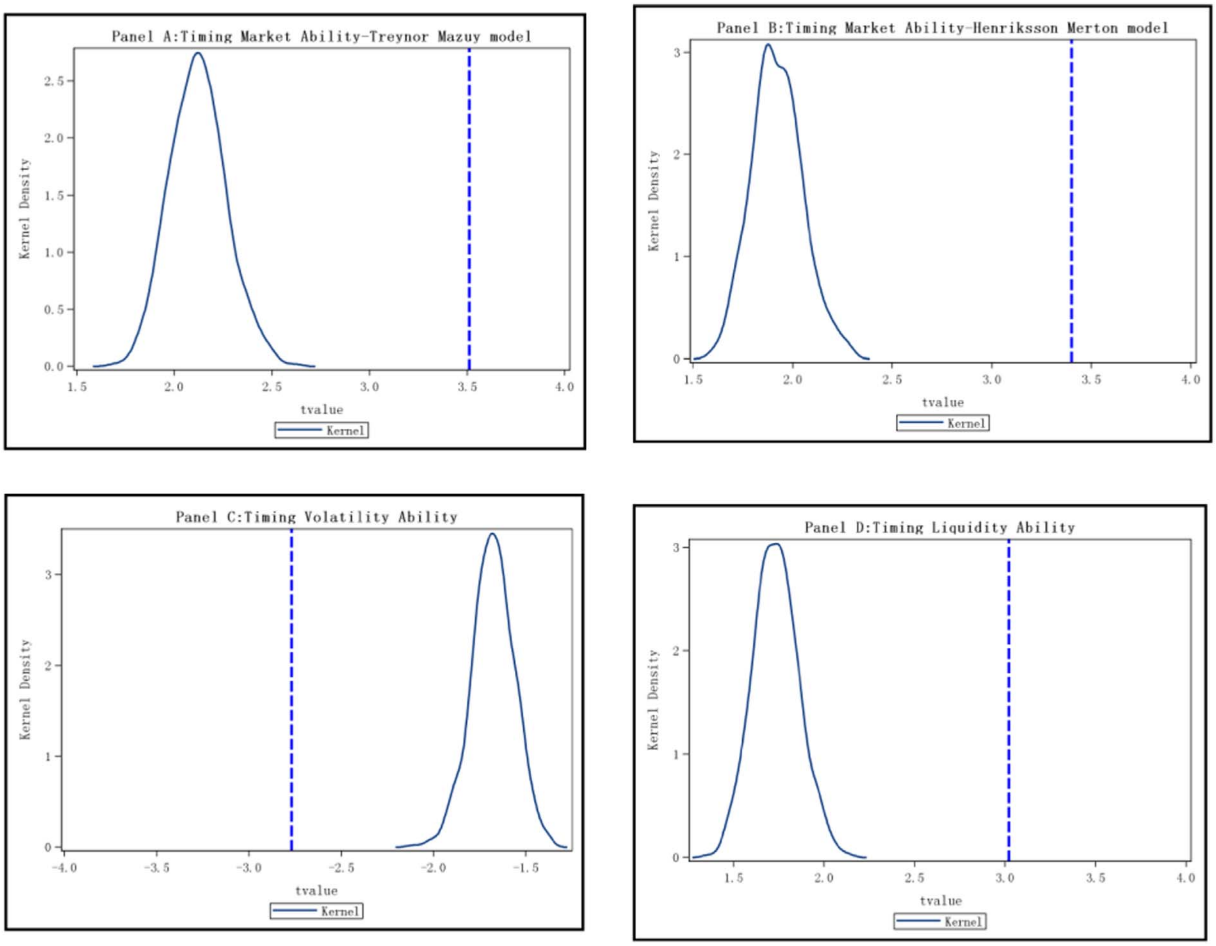

Fig. 3.1. The t-statistics of market timing using the Treynor–Mazuy and Henriksson–Merton models and the volatility-timing and liquidity-timing coefficients for the top 10th percentile, comparing actual funds with bootstrapped funds.
This figure plots the kernel density estimates of the bootstrapped t-statistics of different timing coefficients for the top 10th percentile in each of 1000 bootstrap simulations for the cross section of sample funds (solid lines), as well as the actual t-statistics of different timing coefficients for the top 10th percentile (dashed vertical lines).

measures, respectively. All the results are consistent. In sum, evidence from the bootstrap analysis indicates that top-ranked Chinese mutual fund managers can time market returns, market volatility, and market liquidity.

3.3. Economic value of timing measures

In this section, we aim to answer whether these timing skills can provide significant economic value for investors by examining the investment value of selected top timers. Our empirical work in this section can help investors evaluate the timing skills of Chinese mutual fund managers.

We calculate the timing coefficients in each month for each fund by using the past 36-month estimation period and then form 10 decile portfolios based on their coefficients $\{\gamma_p\}$ for the Treynor–Mazuy market-timing measure, the Henriksson–Merton market-timing measure, the volatility-timing measure, and the liquidity-timing measure, respectively. We then hold these portfolios for three, six, nine, and 12 months, respectively, and calculate their returns based on different levels of timing skills.

Table 4 presents the economic value of the Treynor–Mazuy market-timing ability. The top 10% of market timers have significant alphas in the post-ranking period, while the bottom 10% of market timers do not have significant alphas. The top 10% market timers achieve a return of 1.16% with a t-statistic of 2.93 when the holding period is three months and they can acquire a 0.96% return with a t-statistic of 2.63 when the holding period is 12 months. The top market timers significantly outperform bottom timers by 0.67% when the holding period is three months. However, as the holding period increases, the significance of this outperformance decreases.

Table 5 shows the economic value of Henriksson–Merton market timers. The top 10% of Henriksson–Merton market timers have significant alphas: 1.07, 1.01, 0.95, and 0.91 for holding periods of three, six, nine, and 12 months, respectively. The impact of market timers decreases as the holding period increases. These results are similar to those for Treynor–Mazuy market timers.

Table 6 shows that the volatility timers also have the same performance as market timers. For example, the top 10% of volatility

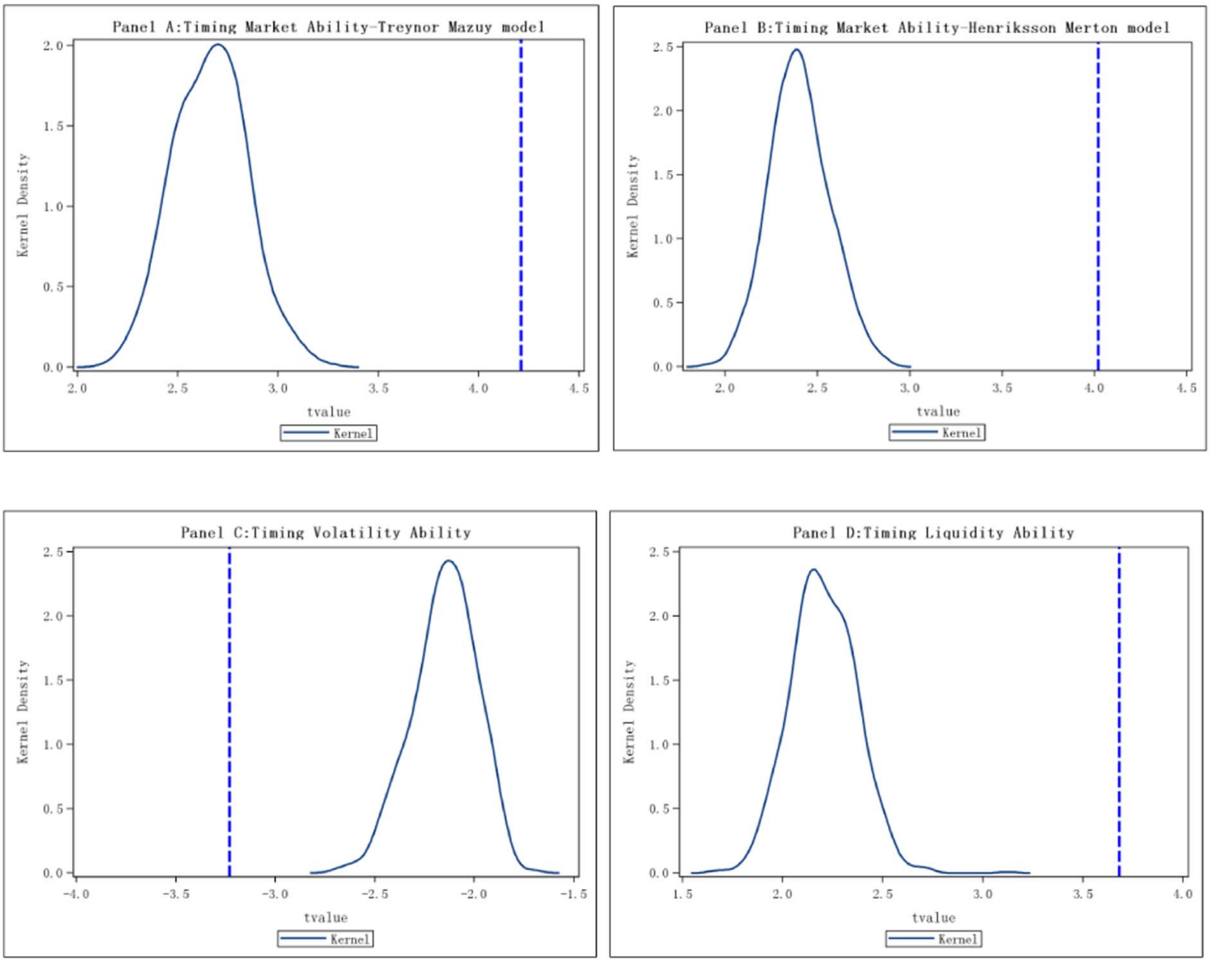

Fig. 3.2. The t-statistics of market timing using the Treynor–Mazuy and Henriksson–Merton models and the volatility-timing and liquidity-timing coefficients for the top 5th percentile, comparing actual funds with bootstrapped funds.
This figure plots the kernel density estimates of the bootstrapped t-statistics of the different timing coefficients for the top fifth percentile in each of 1000 bootstrap simulations for the cross section of sample funds (solid lines), as well as the actual t-statistics of the different timing coefficients for the top fifth percentile (dashed vertical lines).

timers have significant alphas: 0.86, 0.77, 0.71, and 0.66 for holding periods of three, six, nine, and 12 months, respectively. Generally, their performance is weaker than that of market timers.

Table 7 presents the economic value of the liquidity-timing ability. Top liquidity timers also have significant alphas in the post-ranking period, although the alphas decrease as the holding period increases. For example, the top 10% of liquidity timers' portfolios have a significant alpha of 1.14 for a holding period of three months but it decreases to 1.10 after a holding period of 12 months. The bottom timers do not have significant outperformance either.

In sum, we find that the three timing skills indeed add economic value for Chinese mutual fund investors and the timing coefficients reflect the managerial skills in a pragmatic way. These results also indicate that market timing is an effective investment strategy that can provide significant alphas for mutual fund managers.

4. Further analysis

In this section, we test the timing skills results for robustness. We address concerns for the time-series correlation of timing measures, the impact of bond returns, and the shock of the financial crisis. Then, we consider the correlations between the three types of timing abilities. Finally, we examine the timing ability of fund categories with different investment styles separately.

4.1. Controlling for time-series correlation

The bootstrap analysis used in Section 3.2 assumes that the residuals from the timing regressions are independent. However, we are concerned that the residuals could exhibit serial dependence over time. To remove the effects of the serial correlation of residuals,

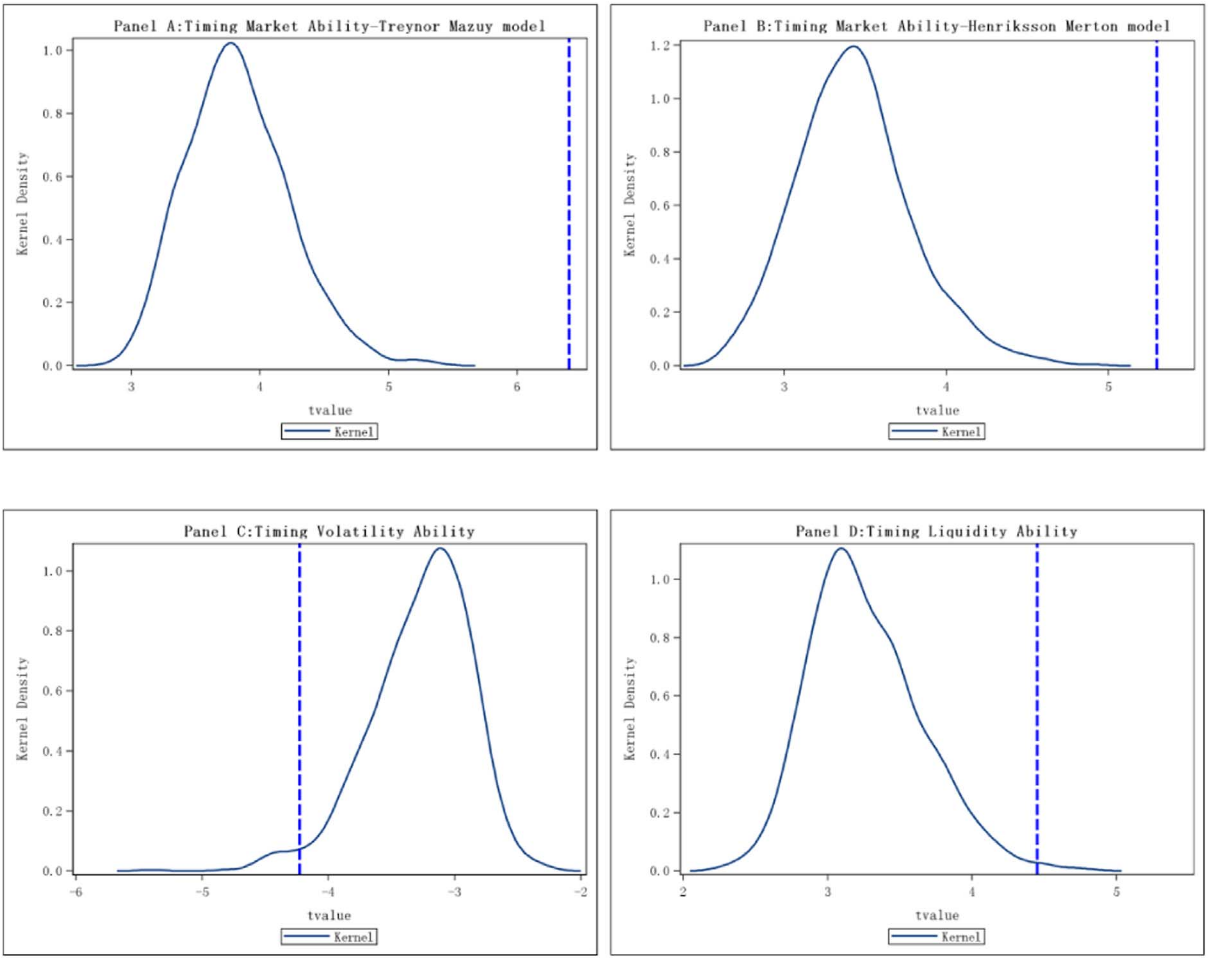

Fig. 3.3. The t-statistics of market timing using the Treynor–Mazuy and Henriksson–Merton models and the volatility-timing and liquidity-timing coefficients for the top first percentile, comparing actual fund with bootstrapped funds.
This figure plots the kernel density estimates of the bootstrapped t-statistics of the different timing coefficients for the top first percentile in each of 1000 bootstrap simulations for the cross section of sample funds (solid lines), as well as the actual t-statistics of the different timing coefficients for the top first percentile (dashed vertical lines).

we conduct a bootstrap analysis by controlling for lagging market conditions in month t using the following equations:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \varepsilon_{p,t}, \quad (10)$$

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \varepsilon_{p,t}, \quad (11)$$

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((V_{m,t} - \overline{V_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \varepsilon_{p,t}. \quad (12)$$

Pástor and Stambaugh's (2003) liquidity measure also indicates that the liquidity risk factor plays an important role in explaining the time series of mutual fund returns. Following prior timing studies (e.g., Cao et al., 2013a, 2013b), we consider an AR(2) process acceptable to estimate the time series of Pástor and Stambaugh's (2003) market liquidity measure. Thus, the following liquidity-timing model includes Pástor and Stambaugh's (2003) liquidity risk factor (LIQ), which is measured as innovations in market liquidity from an AR(2) model:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((L_{m,t} - \overline{L_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \beta_{p,9}LIQ_t + \varepsilon_{p,t}. \quad (13)$$

Table 4
Economic value of market timing using the Treynor–Mazuy model, with evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds at different levels of market-timing skill. In each month, we form 10 decile portfolios based on the funds' market-timing coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different holding periods of K months. The table reports the out-of-sample four-factor alphas (in percent per month) estimated from the post-ranking returns. The t-statistics calculated based on Newey–West heteroskedasticity and autocorrelation-consistent standard errors with one lag are reported in parentheses.

	$K = 3$	6	9	12
Portfolio 1 (top timers)	1.16	1.05	0.97	0.96
	(2.93)	(2.71)	(2.62)	(2.63)
Portfolio 2	0.76	0.79	0.80	0.77
	(2.66)	(2.65)	(2.53)	(2.54)
Portfolio 3	0.69	0.71	0.72	0.70
	(2.73)	(2.73)	(2.79)	(2.78)
Portfolio 4	0.94	0.87	0.85	0.81
	(2.64)	(2.87)	(2.84)	(2.80)
Portfolio 5	0.94	0.91	0.89	0.88
	(3.17)	(3.05)	(3.12)	(3.17)
Portfolio 6	0.51	0.56	0.55	0.54
	(2.05)	(2.30)	(2.34)	(2.38)
Portfolio 7	0.68	0.72	0.70	0.73
	(2.63)	(2.87)	(2.75)	(2.77)
Portfolio 8	0.40	0.43	0.48	0.53
	(1.36)	(1.48)	(1.76)	(1.94)
Portfolio 9	0.67	0.63	0.64	0.66
	(1.98)	(1.90)	(1.78)	(1.80)
Portfolio 10 (bottom timers)	0.49	0.53	0.60	0.65
	(1.37)	(1.51)	(1.63)	(1.68)
Spread (Port. 1–Port. 10)	0.67	0.52	0.36	0.30
	(1.77)	(1.47)	(1.06)	(0.90)

Table 8 reports the distribution of t-statistics of timing measures by controlling for lagging market factors from the bootstrapped samples. The top (1–10%) t-statistics of the market- and liquidity-timing measures still have significant positive and strong t-statistics compared with the previous bootstrap analysis and are even stronger. For example, the top 10% of Chinese mutual funds have $t_{\hat{\gamma}}$ values of 3.81, 3.58, and 3.24 for the Treynor–Mazuy market-timing measure, the Henriksson–Merton market-timing measure, and the liquidity measure, respectively. Previously these measures were 3.51, 3.40, and 3.02, respectively, without controlling for lagged market conditions (Table 3). The volatility-timing measures of the bottom 10% also have stronger and negative t-statistics of − 2.96

Table 5
Economic value of market timing using the Henriksson–Merton model, with evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds at different levels of market-timing skill. In each month, we form 10 decile portfolios based on the funds' market-timing coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different holding periods of K months. The table reports the out-of-sample four-factor alphas (in percent per month) estimated from the post-ranking returns. The t-statistics calculated based on Newey–West heteroskedasticity and autocorrelation-consistent standard errors with one lag are reported in parentheses.

	$K = 3$	6	9	12
Portfolio 1 (top timers)	1.07	1.01	0.95	0.91
	(2.58)	(2.48)	(2.38)	(2.34)
Portfolio 2	0.85	0.78	0.76	0.76
	(3.12)	(2.85)	(2.79)	(2.81)
Portfolio 3	0.77	0.85	0.85	0.82
	(2.77)	(2.92)	(3.09)	(3.04)
Portfolio 4	0.93	0.84	0.84	0.79
	(2.71)	(2.94)	(2.88)	(2.77)
Portfolio 5	0.75	0.73	0.70	0.70
	(2.45)	(2.27)	(2.19)	(2.33)
Portfolio 6	0.61	0.63	0.61	0.61
	(2.95)	(2.95)	(2.96)	(2.95)
Portfolio 7	0.61	0.64	0.67	0.65
	(2.29)	(2.79)	(2.96)	(2.85)
Portfolio 8	0.61	0.64	0.64	0.70
	(1.87)	(2.05)	(2.17)	(2.28)
Portfolio 9	0.62	0.62	0.65	0.70
	(1.88)	(2.00)	(1.98)	(2.14)
Portfolio 10 (bottom timers)	0.46	0.52	0.59	0.62
	(1.32)	(1.42)	(1.51)	(1.51)
Spread (Port. 1–Port. 10)	0.62	0.49	0.36	0.29
	(1.71)	(1.37)	(1.00)	(0.78)

Table 6
Economic value of volatility timing, with evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds at different levels of volatility-timing skill. In each month, we form 10 decile portfolios based on the funds' volatility-timing coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different holding periods of K months. The table reports the out-of-sample four-factor alphas (in percent per month) estimated from the post-ranking returns. The t-statistics calculated based on Newey–West heteroscedasticity and autocorrelation-consistent standard errors with one lag are reported in parentheses.

	$K = 3$	6	9	12
Portfolio 1 (top timers)	0.86	0.77	0.71	0.66
	(2.55)	(2.57)	(2.62)	(2.63)
Portfolio 2	0.68	0.65	0.63	0.62
	(2.23)	(2.34)	(2.21)	(2.12)
Portfolio 3	0.76	0.71	0.75	0.78
	(2.50)	(2.41)	(2.30)	(2.29)
Portfolio 4	0.91	0.79	0.80	0.78
	(2.61)	(2.67)	(2.79)	(2.79)
Portfolio 5	0.92	0.87	0.85	0.86
	(2.70)	(2.86)	(2.88)	(2.88)
Portfolio 6	0.69	0.71	0.68	0.68
	(2.41)	(2.43)	(2.29)	(2.37)
Portfolio 7	0.80	0.84	0.84	0.86
	(2.81)	(2.91)	(3.04)	(3.14)
Portfolio 8	0.54	0.58	0.53	0.58
	(2.08)	(2.12)	(2.02)	(2.23)
Portfolio 9	0.67	0.71	0.78	0.80
	(2.82)	(2.87)	(3.12)	(3.11)
Portfolio 10 (bottom timers)	0.34	0.49	0.54	0.47
	(1.53)	(1.90)	(1.85)	(1.55)
Spread (Port. 1–Port. 10)	0.52	0.28	0.16	0.19
	(2.14)	(1.39)	(0.81)	(0.87)

(− 2.77 in Table 3). Even after the time series influence is considered, the top-ranked Chinese mutual fund managers still show significant t-statistics for timing ability.

4.2. Controlling for bond market conditions

We construct timing models based on the standard Carhart (1997) four-factor model; however, many Chinese equity-oriented and

Table 7
Economic value of liquidity timing, with evidence from out-of-sample alphas.

This table presents the out-of-sample alphas for the portfolios consisting of funds at different levels of liquidity-timing skill. In each month, we form 10 decile portfolios based on the funds' liquidity-timing coefficients estimated from the past 36 months (i.e., ranking period) and then hold these portfolios for different holding periods of K months. The table reports the out-of-sample four-factor alphas (in percent per month) estimated from the post-ranking returns. The t-statistics calculated based on Newey–West heteroscedasticity and autocorrelation-consistent standard errors with one lag are reported in parentheses.

	$K = 3$	6	9	12
Portfolio 1 (top timers)	1.14	1.18	1.11	1.10
	(3.08)	(2.96)	(2.74)	(2.73)
Portfolio 2	0.83	0.71	0.67	0.65
	(2.89)	(2.61)	(2.44)	(2.36)
Portfolio 3	0.78	0.79	0.81	0.80
	(2.80)	(2.83)	(2.86)	(2.74)
Portfolio 4	0.71	0.73	0.66	0.60
	(2.20)	(2.65)	(2.49)	(2.50)
Portfolio 5	0.70	0.67	0.62	0.58
	(2.91)	(2.78)	(2.78)	(2.73)
Portfolio 6	0.54	0.59	0.63	0.67
	(2.58)	(2.78)	(2.95)	(3.03)
Portfolio 7	0.75	0.77	0.77	0.79
	(2.83)	(2.87)	(2.81)	(2.92)
Portfolio 8	0.66	0.68	0.72	0.75
	(2.21)	(2.30)	(2.33)	(2.35)
Portfolio 9	0.54	0.61	0.70	0.76
	(1.75)	(1.74)	(1.91)	(2.04)
Portfolio 10 (bottom timers)	0.57	0.53	0.53	0.54
	(1.25)	(1.37)	(1.42)	(1.42)
Spread (Port. 1–Port. 10)	0.57	0.65	0.58	0.57
	(1.59)	(2.59)	(2.53)	(2.61)

Table 8
This table presents the results of the bootstrap analysis of market timing, volatility timing, and liquidity timing, controlling for time series correlation. For each fund with at least 36 monthly return observations, we estimate the Treynor–Mazuy market-timing model,

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

the Henriksson–Merton market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \varepsilon_{p,t};$$

the volatility-timing model,

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

and the liquidity-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(L_{m,t} - \overline{L_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}MKT_{t-1} + \beta_{p,6}SMB_{t-1} + \beta_{p,7}HML_{t-1} + \beta_{p,8}MOM_{t-1} + \beta_{p,9}LIQ_t + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include the market excess return (MKT), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (MOM). The term MKT_t^2 is the square of the monthly market excess return in month t, $V_{m,t}$ is the market volatility-timing measure in month t, $\overline{V_m}$ is the mean of market volatility, $L_{m,t}$ is the market liquidity measure in month t, $\overline{L_m}$ is the mean of market liquidity, and LIQ_t is the Pástor–Stambaugh (2003) liquidity risk factor for month t, measured as innovations in market liquidity from an AR(2) model. The coefficient γ_p measures liquidity-timing ability. The first row reports the sorted t-statistics of the timing coefficients across individual funds in each timing model and the second row shows the empirical p-values from the bootstrap simulations. The number of resampling iterations is 1000.

		Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
		1%	3%	5%	10%	10%	5%	3%	1%
Market timing	t-Stat	− 2.57	− 1.83	− 1.53	− 0.90	3.81	4.69	5.09	6.81
Treynor model	p-Value	0.18	0.23	0.28	0.91	0.00	0.00	0.00	0.00
Market timing	t-Stat	− 2.37	− 1.60	− 1.28	− 0.71	3.58	4.13	4.58	5.32
Henriksson model	p-Value	0.45	0.85	0.97	1.00	0.00	0.00	0.00	0.00
Volatility timing	t-Stat	− 4.34	− 3.71	− 3.60	− 2.96	0.62	1.19	1.66	2.50
	p-Value	0.00	0.00	0.00	0.00	1.00	0.99	0.68	0.18
Liquidity timing	t-Stat	− 2.50	− 1.83	− 1.41	− 1.08	3.24	3.77	4.18	4.89
	p-Value	0.99	1.00	1.00	1.00	0.00	0.00	0.00	0.00

mixed mutual funds also invest in the bond markets. The returns on the bond markets should also be considered part of market conditions; thus, we add the monthly Treasury bond yield change to the market controls:

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t}, \quad (14)$$

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t}, \quad (15)$$

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((V_{m,t} - \overline{V_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t}, \quad (16)$$

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t((L_{m,t} - \overline{L_m})) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}LIQ_t + \beta_{p,11}BOND_{t-1} + \varepsilon_{p,t}. \quad (17)$$

Table 9 reports the distribution of the t-statistics of the timing measures from Eqs. (14) to (17). Comparing the results in Table 9 with those in Tables 3 and 8, we find that the evidence of timing measures remains unchanged after we control for bond market conditions and the liquidity risk factor. For example, the top 10% Treynor–Mazuy market timers have a significant positive t-statistic of 4.00, which is slightly greater than the 3.81 reported in Table 8 and greater than the 3.51 reported in Table 3, with a p-value still close to zero. The results of other timing measures are also consistent with the previous ones in Tables 3 and 8.

4.3. Excluding the 2008–2009 crisis period

In the crisis period from 2008 to 2009, the Chinese stock market confronted dramatic changes. To exclude the influence of extreme market conditions, we remove the 2008–2009 financial crisis period from our sample to examine the timing measures. A bootstrap analysis is conducted for Eqs. (14) to (17) using the revised sample and the results are shown in Table 10. The results

Table 9
This table presents the results of the bootstrap analysis of market timing, volatility timing, and liquidity timing, controlling for bond returns. For each fund with at least 36 monthly return observations, we estimate the Treynor–Mazuy market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

the Henriksson–Merton market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

the volatility-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(V_{m,t} - \overline{V_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

and the liquidity-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(L_{m,t} - \overline{L_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}LIQ_t + \beta_{p,11}BOND_{t-1} + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include the market excess return (MKT), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (MOM). The term MKT_t^2 is the square of the monthly market excess return in month t, $V_{m,t}$ is the market volatility-timing measure in month t, $\overline{V_m}$ is the mean of market volatility, $L_{m,t}$ is the market liquidity measure in month t, $\overline{L_m}$ is the mean of market liquidity, and LIQ_t is the Pástor–Stambaugh (2003) liquidity risk factor for month t, measured as innovations in market liquidity from an AR(2) model. The coefficient γ_p measures liquidity-timing ability. The first row reports the sorted t-statistics of the timing coefficients across individual funds in each timing model and the second row shows the empirical p-values from the bootstrap simulations. The number of resampling iterations is 1000.

		Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
		1%	3%	5%	10%	10%	5%	3%	1%
Market timing	t-Stat	− 3.40	− 1.82	− 1.62	− 1.12	4.00	4.75	5.17	7.13
Treynor model	p-Value	0.00	0.34	0.15	0.30	0.00	0.00	0.00	0.00
Market timing	t-Stat	− 2.77	− 1.65	− 1.29	− 0.74	3.66	4.38	4.73	5.52
Henriksson model	p-Value	0.05	0.65	0.93	1.00	0.00	0.00	0.00	0.00
Volatility timing	t-Stat	− 4.48	− 3.58	− 3.35	− 2.86	0.63	1.23	1.71	2.47
	p-Value	0.00	0.00	0.00	0.00	1.00	1.00	0.87	0.52
Liquidity timing	t-Stat	− 2.92	− 1.87	− 1.57	− 1.10	3.25	3.85	4.11	5.04
	p-Value	0.18	0.70	0.77	0.93	0.00	0.00	0.00	0.00

indicate that the top Chinese mutual fund timers still deliver strong and positive timing skills. For example, the top 10% Treynor–Mazuy market timers have a significant positive t-statistic of 3.98, which is similar to the 4.00 reported in Table 9. The Henriksson–Merton timing measures and liquidity timing measures are also consistent with previous results. The bottom 10% of volatility market timers have a significant negative t-statistic of − 2.10, which is slightly lower in magnitude than the − 2.86 in Table 9.

4.4. Correlations between the three timing abilities

In this section, we document the correlations between fund managers' abilities to time market returns, volatility and liquidity, and derive some findings. We sort the whole sample into five equal groups based on the t-statistics of market, volatility and liquidity timing coefficients, respectively.

In Table 11, within each timing group, we present the percentage of t-statistics of the other three timing measures exceeding the indicated cutoff values. The results suggest that each timing measure is positively relevant to the other three timing measures. Specifically, in regard to market timing, we find that funds in the high market-timing groups exhibit high proportions of funds with volatility- and liquidity-timing abilities. In addition, market-return timing ability is more related to liquidity timing ability than volatility timing ability. However, the relevance between volatility timing ability and liquidity timing ability is weak.

We also conduct a correlation analysis between t-statistics of the three timing coefficients and the results are consistent. Specifically, the correlation coefficients between Treynor–Mazuy and Henriksson–Merton market timing and liquidity timing abilities are 0.798 and 0.747, respectively. The correlation coefficients between Treynor–Mazuy and Henriksson–Merton market timing and volatility timing ability are slightly small, with 0.492 and 0.484. However, the correlation coefficient between volatility and liquidity timing ability is merely 0.237.

These correlations can be interpreted from several aspects. First, in general, the correlations between the three timing abilities are all positive, suggesting that when a mutual fund manager has one aspect of timing ability, he is more likely to possess the other two

Table 10
This table presents the results of the bootstrap analysis of market timing, volatility timing, and liquidity timing, excluding the 2008–2009 crisis period. For each fund with at least 36 monthly return observations, we exclude the 2008–2009 financial crisis period and estimate the Treynor–Mazuy market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t^2 + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

the Henriksson–Merton market-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p Max(MKT_t, 0) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

the volatility-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(V_{m,t} - \overline{V_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}BOND_{t-1} + \varepsilon_{p,t};$$

and the liquidity-timing model,

$$r_{p,t} = \alpha_p + \beta_{p,1}MKT_t + \gamma_p MKT_t(L_{m,t} - \overline{L_m}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}MOM_t + \beta_{p,5}BOND_t + \beta_{p,6}MKT_{t-1} + \beta_{p,7}SMB_{t-1} + \beta_{p,8}HML_{t-1} + \beta_{p,9}MOM_{t-1} + \beta_{p,10}LIQ_t + \beta_{p,11}BOND_{t-1} + \varepsilon_{p,t},$$

where $r_{p,t}$ is the excess return on each individual fund in month t. The independent variables include the market excess return (MKT), a size factor (SMB), a book-to-market value factor (HML), and a momentum factor (MOM). The term MKT_t^2 is the square of the monthly market excess return in month t, $V_{m,t}$ is the market volatility-timing measure in month t, $\overline{V_m}$ is the mean of market volatility, $L_{m,t}$ is the market liquidity measure in month t, $\overline{L_m}$ is the mean of market liquidity, and LIQ_t is the Pástor–Stambaugh (2003) liquidity risk factor for month t, measured as innovations in market liquidity from an AR(2) model. The coefficient γ_p measures liquidity-timing ability. The first row reports the sorted t-statistics of the timing coefficients across individual funds for each timing ability and the second row shows the empirical p-values from the bootstrap simulations. The number of resampling iterations is 1000.

		Bottom t-statistics for $\hat{\gamma}$				Top t-statistics for $\hat{\gamma}$			
		1%	3%	5%	10%	10%	5%	3%	1%
Market timing	t-Stat	− 2.99	− 2.59	− 2.43	− 1.72	3.98	4.80	5.36	7.65
Treynor model	p-Value	0.38	0.05	0.01	0.06	0.00	0.00	0.00	0.00
Market timing	t-Stat	− 2.10	− 1.41	− 1.18	− 0.97	3.92	5.28	5.39	5.89
Henriksson model	p-Value	0.96	1.00	1.00	1.00	0.00	0.00	0.00	0.00
Volatility timing	t-Stat	− 3.43	− 3.22	− 2.65	− 2.10	1.05	2.09	2.34	3.67
	p-Value	0.04	0.00	0.00	0.00	1.00	0.17	0.24	0.05
Liquidity timing	t-Stat	− 3.64	− 2.92	− 2.77	− 2.41	2.97	3.77	4.59	6.11
	p-Value	0.10	0.02	0.00	0.00	0.00	0.00	0.00	0.00

aspects of timing abilities. Existing papers have proved that market liquidity comoves with market returns and predicts future returns (e.g., Amihud, 2002; Acharya and Pedersen, 2005). As an example, market-wide liquid deteriorates during the 2008 financial crisis was accompanied by a collapse in U.S. market-wide stock prices. Thus, a manager who is capable of forecasting the market-wide liquidity correctly are more likely to forecast the market returns and adjust his portfolio exposure, and vice versa. In addition, the possible explanation for the less strong relationship between volatility and other two types of timing abilities is that some good market return or liquidity timers have incentives to respond to volatility adversely, by increasing funds' exposures when volatility is predicted to be high, documented by Ferson and Mo (2016). The reason is that the relation between fund managers' payoffs and the fund's performance is usually option-like or convex. Therefore, the adverse volatility-related behaviors of some good market return or liquidity timers lead to the slightly weaker relationship between volatility and other two types of timing skills.

4.5. Investment style and timing

Thus far, we find that there are many Chinese mutual funds exhibiting successful timing ability. However, one possibility is that the significant timing abilities are driven by some funds with specific investment styles. For example, Giambona and Golec (2009) document a significant relation between the direction of volatility timing and fund investment style and they find conservative funds become more aggressive when market volatility is high. Understanding whether different investment-style categories lead to different results for timing could be meaningful for both researchers and investors. To investigate if timing abilities vary with fund investment style, we categorize our sample funds by investment styles into 181 growth funds, 43 blend funds, and 56 value funds.[6] Then we repeat the tests of Table 2 for the three fund categories separately.

[6] Data source: CSMAR Database.

Table 11
This table presents the correlations between fund managers' abilities to time market returns, volatility and liquidity. We sort the whole sample into five equal groups based on the t-statistics of market, volatility and liquidity timing coefficients, respectively. We repeat the tests of Table 2 for the fund categories separately. Within each timing group, we present the percentage of t-statistics of the other three timing measures exceeding the indicated cutoff values.

Market timing-Treynor model	N	Market Henriksson (t > = 1.645)	Volatility (t < = - 1.645)	Liquidity (t > = 1.645)
Low	56	0.00	3.57	1.79
2	56	0.00	23.21	0.00
3	56	12.50	25.00	17.86
4	56	85.71	53.57	39.29
High	56	100.00	51.79	87.50
Market timing-Henriksson model	**N**	**Market Treynor (t > = 1.645)**	**Volatility (t < = - 1.645)**	**Liquidity (t > = 1.645)**
Low	56	0.00	8.93	1.79
2	56	0.00	16.07	3.57
3	56	5.36	28.57	19.64
4	56	73.21	51.79	32.14
High	56	100.00	51.79	89.29
Volatility timing	**N**	**Market Treynor (t > = 1.645)**	**Market Henriksson (t > = 1.645)**	**Liquidity (t > = 1.645)**
Low	56	67.86	75.00	42.86
2	56	41.07	48.21	35.71
3	56	30.36	28.57	26.79
4	56	26.79	32.14	23.21
High	56	12.50	14.29	17.86
Liquidity timing	**N**	**Market Treynor (t > = 1.645)**	**Market Henriksson (t > = 1.645)**	**Volatility (t < = - 1.645)**
Low	56	0.00	1.79	10.71
2	56	3.57	5.36	25.00
3	56	21.43	33.93	33.93
4	56	64.29	69.64	46.43
High	56	89.29	87.50	41.07

Like Table 2, we present the percentage of t-statistics exceeding the different indicated cutoff values for the three subsamples separately. As shown in Table 12, in the case of the Treynor–Mazuy market-timing model, the percentages of growth, blend and value funds that demonstrate true market timing ability at the 10% level are 39.53%, 33.70%, and 39.29%, respectively. In sum, there is no

Table 12
This table presents the distribution of t-statistics for the timing coefficients of growth, blend, value funds, respectively. The sample funds are categorized by investment styles into three groups, including 181 growth funds, 43 blend funds, and 56 value funds. The timing models that we use are the same as those in Table 2. This table reports the percentage of t-statistics exceeding the indicated cutoff values for the three subsamples separately.

	Percentage of funds					
	$t \leq -2.326$	$t \leq -1.960$	$t \leq -1.645$	$t \geq 1.645$	$t \geq 1.960$	$t \geq 2.326$
Market timing, Treynor						
Growth (181)	0.00	0.00	0.00	39.53	25.58	20.93
Blend (43)	1.66	1.66	2.21	33.70	28.18	21.55
Value (56)	0.00	0.00	0.00	39.29	32.14	25.00
Market timing, Henriksson						
Growth (181)	0.00	2.21	3.31	38.12	31.49	23.76
Blend (43)	0.00	0.00	2.33	48.84	39.53	23.26
Value (56)	0.00	0.00	0.00	37.50	35.71	26.79
Volatility timing						
Growth (181)	14.92	20.99	27.62	3.31	2.21	1.10
Blend (43)	16.28	30.23	44.19	0.00	0.00	0.00
Value (56)	21.43	28.57	33.93	3.57	3.57	3.57
Liquidity timing						
Growth (181)	0.55	1.10	1.66	29.83	23.76	16.57
Blend (43)	0.00	0.00	0.00	20.93	13.95	13.95
Value (56)	0.00	0.00	0.00	33.93	25.00	17.86

dramatic difference in the three timing abilities across the three types of funds, indicating that our main results are not driven by funds with specific investment styles.

5. Conclusion

We investigate the market-timing, volatility-timing, and liquidity-timing abilities of Chinese mutual fund managers. We use cross-sectional and bootstrap analyses and find strong evidence that Chinese mutual fund managers have timing skills. They increase (reduce) market exposure when the Chinese equity market advances (declines) or when the market exhibits less (more) volatility or more liquidity (illiquidity). In addition, the top timing funds outperform the bottom timing funds. These results indicate that the top Chinese mutual fund timers can add value for investors and timing measures can be important in Chinese mutual fund alphas.

We also conduct robustness checks of our findings and show that our inferences about timing measures hold in all the tests. Finally, timing measures are important in investment decision-making processes. Our findings regarding Chinese mutual fund managers' timing skills can boost investor confidence to invest in Chinese mutual funds.

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