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Abstract

This study investigate the profitability of momentum and reversal strategies of different investment horizons in the Chinese stock market. The findings indicate that momentum strategies are profitable for investment horizons less than one week. For longer investment horizons, reversal strategies are profitable. This result is very different from the US market, where profitable momentum strategies yield to much longer investment horizons. We show that this is because investors are generally overreact to the company cash flow news in China while underreact to cash flow news in the US.

Keywords: momentum, reversal, overreaction, stock market

JEL Classification: D01, C14, C50, G11, G32

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Investment Horizons and the Profitability of Momentum and Reversal Strategies in the Chinese Stock Market

1. Introduction

According to the efficient market hypothesis, past stock returns should have no effect on current stock returns. However, two stock trading strategies which are based on past stock returns are found to be profitable in the literature. These are the momentum and reversal strategies. Momentum strategies buy stocks with high past returns (winners) and sell stocks with low past returns (losers). Reversal strategies buy past losers and sell past winners. The profitability of momentum and reversal strategies is found to be related to the investment horizons in the US stock market. Specifically, momentum strategies are profitable over investment horizons as long as one year in the US market (Levy, 1967; Jegadeesh and Titman, 1993; Griffin *et al*, 2003; Asness and Moskowitz, 2013). Reversal strategies are profitable over horizons longer than one year (De Bondt and Thaler, 1985, 1987; Jegadeesh, 1990; Lehmann, 1990). Theoretical models explain the short-run momentum profitability by irrational investors' underreaction to company cash flow news (Barberis *et al*., 1998; Hong and Stein, 1999). In other words, if investors underreact to cash flow news, stock returns increase less than one percent when company fundamental values increase by one percent. This would motivate arbitragers to make profits by buying the undervalued stocks. The buying orders will further push up the price. Momentum strategies, as a result, benefit from the continuation price trend generated by the orders of the arbitragers. Traders who follow the momentum strategies can earn profit from the short-run continuation trend, but they could also bid up prices to levels higher than the stock fundamental values (Hong and Stein, 1999). Therefore, a price increase which is triggered by positive company cash flow news may go too far. As stock prices eventually converge to their fundamental values, reversal strategies then make profits by selling the overpriced stocks. Cohen *et al*. (2002) find that the US investors underreact to cash flows at the quarterly frequency. Since momentum strategies are profitable for an investment horizon of one quarter in the US, their funding is taken as supporting evidence for the theoretical models.

Past literature has studied the profitability of momentum and reversal strategies in the Chinese stock market.[2] However, the existing studies use different sample periods and investment horizons, which make the results incomparable. Therefore, it is difficult to draw a conclusion on the relationship between investment horizons and the profitability of the momentum and reversal strategies in the Chinese stock market. Moreover, there has been no study on the investors' reaction to cash flow news in China, leaving the profitability of the momentum and reversal strategies unexplained.

In this paper, we study the profitability of the momentum and reversal strategies of different investment horizons in the Chinese stock market using a sample from 2006 to 2017. We find that, compared to the US stock market, momentum strategies are only profitable for very short horizons (as long as one week) in the Chinese stock market. For horizons longer than one week, reversal strategies are profitable. Moreover, empirical study indicates investors in the Chinese stock market overreact to cash flow news.

The contrasting results between China and the US can be explained by the differences in the proportion of individual investors between China and the US. As is well known, the US stock market is dominated by institutional investors who are more rational than individual investors (Cohen *et al.*, 2002). In contrast, individual investors dominate the Chinese A-share market, while professional institutional investors hold less than 35%[3] of the total market value. In other words, the proportion of irrational investors is much higher in the Chinese stock market than in the US stock market.

Behavioural models of Barberis *et al.* (1998) and Hong and Stein (1999) assume that all investors are irrational and neglect the role of rational institutional investors. Suppose the stock price is determined by the average valuation of all investors, then we can express the stock price by

$$p = w^{ir}p^{ir} + w^{r}p^{r},$$

where p is the stock price, w^{ir}, p^{ir}, w^{r}, p^{r} are respectively the proportion of irrational investors, the stock valuation by the representative irrational investor, the

[2] Wang (2004); Naughton *et al.* (2008); Wu (2011); Tan (2012); Pan *et al.* (2013); Cheema and Nartea (2014); Choudhry and Wu (2015); Wu (2016); Zhang *et al.*(2018); Zhang *et al.* (2019). In a related study, Xue and Zhang (2017) find that stock returns in China is autocorrelated and the autocorrelation is stronger when investor sentiment is high.

[3] The data is as of the end of 2017, from China Securities Depository and Clearing Co. Ltd.

proportion of rational investors, and the stock valuation by the representative rational investor. Following the literature, we assume that irrational investors underreact to cash flow news. This means that if the company cash flow surprisingly increases by one percent, p^{ir} increase less than one percent. If all investors are irrational, i.e., $w^{ir} = 1$, the stock price increases less than one percent. Our results that investors on average overreact to cash flow news suggest that the stock price increases more than one percent if cash flow increases by one percent. This can only happen if $w^{ir} < 1$ and p^{r} increases more than one percent. That is, rational investors overreact to cash flow news.

Abreu and Brunnermeier (2003) show that rational institutional investors overreact to cash flow news if irrational investors misprice stocks. This is because rational investors have heterogeneous belief about the mispricing of stocks and coordination is needed for them to successfully correct the mispricing. Company cash flow news serve as coordinating signals for collective actions by the rational investors. Therefore, when company cash flow news arrives, rational investors not only react to its information contents about the company's fundamental value but also react to its signal of collective actions. As a result, rational investors overreact to cash flow news.

More severe mispricing suggests that the potential gain from joining the collective correction of the stock price is larger. Therefore, rational investors are more sensitive to signals of collective actions if the mispricing is more severe. In other words, rational investors' overreaction to cash flow news is stronger if the mispricing is more severe. Since stock mispricing grows larger and lasts longer when there are more irrational investors, rational investors' overreaction to cash flow news is stronger when there are more irrational investors. Therefore, a larger proportion of irrational investors have two offsetting effects. On the one hand, it raises the proportion of investors who underreact to cash flow news due to their behavioural biases. On the other hand, it increases the strength of overreaction to cash flow news by rational investors. When the second effect dominates, investors on average overreact to cash flow news if the proportion of irrational investors is large. Our empirical results suggest that this is the case in the Chinese stock market.

To see how the second effect can dominate, we use the following example for illustration: suppose that a stock price is 20 dollars. Irrational investors believe the price matches the fundamental value. Some rational investors notice that the stock's fundamental value is just 10 dollars given the current information on the future cash flows of the company. But they are not sure whether other rational investors have noticed the mispricing, so they wait for a coordinating signal before starting short selling the stock. Suddenly, a piece of negative news comes, suggesting that future company cash flows will decline by 10 percent. The news is a public signal so that all investors see it. Irrational investors reduce their valuation of the stock from 20 dollars to 18 dollars if they fully react to the cash flow news. Assume that their degree of underreaction is severe, so a 10-percent decrease in the future cash flows only cuts their valuation of the stock by 5 percent. Therefore, their valuation of the stock changes to 19 dollars. Rational investors readjust their valuation of the fundamental value of the stock by 10 percent to 9 dollars. Moreover, because the negative company news is taken as a coordinating signal for selling. They starts to short sell the stock and the targeting price is 9 dollars. The gap between the current stock price and the target price of irrational and rational investors are respectively 1 dollars and 11 dollars. Let the proportion of irrational investors be 2/3 (which is close to the proportion of stock values held by individual investors in China). The new stock price after the selling of both types of investors is $19 \times \frac{2}{3} + 9 \times \frac{1}{3} = 15\frac{2}{3}$. The stock price declines by 21.7 percent, which is much higher than the 10 percent decline in the fundamental value suggested by the news. Investors on average overreact to cash flow news, though the irrational investors underreact to cash flow news. Note that the average overreaction is strong because the mispricing is large. Suppose the mispricing is not that severe, say the initial stock price is 15 dollars while the fundamental value evaluated by rational investors is 10 dollars. Then in the above example, the stock price after the news about a 10-percent decline in the future cash flows is $14\frac{1}{4} \times \frac{2}{3} + 9 \times \frac{1}{3} = 12\frac{1}{2}$. The stock price declines by 16.7 percent from 15 dollars. Although investors still on average overreact to cash flow news, the overreaction is not as severe as when the initial mispricing is larger. As suggested by Abreu and Brunnermeier (2003), the mispricing is more severe when there are more irrational investors. Using an example from the Chinese warrant market, Xiong and Yu (2011) show that when individual investors prevail, asset price can indeed be severely distorted.

The remainder of this paper is organized as follows: Section 2 provides a brief institutional background; Section 3 outlines the methodology; Section 4 contains a brief description of the dataset; Section 5 shows the empirical performance of the momentum and reversal strategies, and tests investors' reaction to company cash flow news; and Section 6 concludes the paper.

2. Institutional background

The Chinese stock market has expanded dramatically in the past decade, as it is based in a fast-growing developing country. The Non-tradable Share Reform in 2005 liquidized all shares of state-owned enterprises (SOEs). By the end of 2017, the total market capitalization of the Chinese stock market hit 56.7 trillion RMB (about 9 trillion US dollars), growing six-fold since 2006 (8.9 trillion RMB) and coming only second to the US stock market. There are currently 3,512 listed companies on the Chinese stock market, up from only 1,421 in 2006 (Gang *et al.*, 2019).

The Chinese stock market is officially separated into three segmented markets (or three boards) according to the size of the listed companies: the large-cap market (Large-Cap), the small and medium-sized enterprise (SME) market, and the growth enterprise (GE) market. According to Chinese securities regulations, companies listed on different markets are subject to different preconditions when launching initial public offerings (IPOs). Specifically, the Large-Cap market has stricter rules on share capital size, profitability, and minimum market value. Therefore, Large-Cap companies are mostly big enterprises, including most of the country's SOEs, with large capital scale and stable profitability. The SME market, on the contrary, requires much lower share capital. As a result, SME companies are often much smaller in terms of market value relative to the Large-Caps. The GE market essentially provides an additional market for even smaller companies that cannot meet the preconditions of the Large-Cap and SME markets. The GEs are often emerging companies that are temporarily unstable in their business operations. Currently, the GE market has the most lenient listing requirements, and therefore it is exposed to the highest market risk relative to the others. Furthermore, the industries represented in the three markets differ. Large-Cap companies mostly belong to traditional industries (banking, manufacturing, natural resource, etc.) while companies in the SME and GE markets are mainly high-tech companies.

In short, these three institutionally segmented markets are different in their listing requirements, trading regulations and supervision mechanisms. Therefore, it is likely that they demonstrate very different reactions to the cash flow news.

The Chinese A-share stock market is dominated by small individual (or retail) investors. Before the second quarter of 2017, professional institutional investors never held more than 29% of the total market value. Although the share of professional institutional investors in China had increased to 35% by the end of 2017, that figure remains dwarfed by the proportion of individual investors.[4] Moreover, the majority of individual investors in China hold very small positions. Table A1 shows the distribution of different investors in the Chinese A-share stock market in terms of market value. About 72% of individual investors hold assets (cash and stocks) worth less than 100,000 RMB in market value, and 93% of individual investors hold assets (cash and stocks) worth less than 500,000 RMB in market value.

3. Methodology

3.1 Trading strategies

This paper follows the approach taken by Jegadeesh and Titman (1993) to find profitable trading strategies. Past literature in this area suggests that different information sets or holding periods affect outcomes. This paper looks at three different investment frequencies. At the monthly frequency, it builds a total of 16 strategies conditional on their realized averaged returns over the previous one, three, six and nine months (four information sets altogether), as well as under four holding periods ranging from one, three, six to nine months. This study combines each of the information sets (defined as J) together with each of the holding lengths (defined as K) into one trading strategy. This trading strategy is therefore denoted as a J/K strategy. Each J/K strategy is constructed by taking the following three steps.

Step one: In each month, denoted as T, stocks are ranked in an ascending order in terms of their geometric average returns in the past J month. The calculation is as follows:

[4] Data is from China Securities Depository and Clearing Corp. Ltd., and the Wind database.

$$R_{i,T-J} = \sqrt[J]{\prod_{T-J}^{T-1}\left(1+R_{i,t}\right)}-1 \tag{1}$$

where $R_{i,t}$ is the return of stock i at time t; and $R_{i,T-J}$ represents the performance of the stock in the past J months.

Step two: In every month T, after the ranking of performances in the first step, a bundle of the top n securities (with the lowest returns) is denoted as a loser portfolio, and the bottom n stocks form a winner portfolio. The value of n is determined by the relative size of the corresponding market or market segments. Each constituent stock is assigned an equal weight within the portfolio to which it belongs.

Step three: In any given month T, a long position on the winner portfolio and simultaneously a short position on the loser portfolio are taken. Both positions are held for K months, after which the resulting return is calculated as follows:

$$\begin{aligned} R_T^{J,K} &= \sum_{i=1}^{n} R_{i,T,K}^{W} - \sum_{j=1}^{n} R_{s,T,K}^{L} \\ &= \sum_{i=1}^{n}\left[\sqrt[K]{\prod_{t=T}^{T+K}\left(1+R_{i,t}^{W}\right)-1}\right] - \sum_{s=1}^{n}\left[\sqrt[K]{\prod_{t=T}^{T+K}\left(1+R_{s,t}^{L}\right)-1}\right] \end{aligned} \tag{2}$$

where $R_{i,T,K}^{W}$ or $R_{s,T,K}^{L}$ stand for the return of a given stock portfolio and the superscripts W or L represent holding the winner or loser portfolio for K months at time T. K and T are the subscripts as shown. Therefore, a representation of $R_T^{J,K}$ can be seen as a net return from the J/K strategy at time T.

Furthermore, profit margins are generated by implementing the above strategy for a certain period of time. The equation used to calculate the average return of each strategy is then:

$$R^{J,K} = \frac{1}{\left(S-K+1-J\right)} \sum_{T=J}^{S-K+1} R_T^{J,K} \tag{3}$$

where $R_T^{J,K}$ denotes the return of J/K strategies at month T; $R^{J,K}$ denotes the average return of the J/K strategy over the time period; and S is the total length of the time series.

This paper constructs the weekly and daily momentum strategies by following similar steps. For the weekly frequency, it considers formation periods of the previous one, two, three, and four weeks, and holding periods of one, two, three, and four weeks. For the daily frequency, it considers formation periods of past one, two, three, and four days, and holding periods of one, two, three, and four days.

3.2 Decomposing the stock return

This paper follows the methodology introduced by Campbell (1991), Vuolteenaho (2002) and Cohen *et al.* (2002) to decompose the unexpected stock return into an expected-return component and a cash flow component:

$$\begin{aligned} r_t - E_{t-1}\left(r_t\right) &= \Delta E_t\left(\sum_{j=0}^{\infty}\rho^j e_{t+j}\right) - \Delta E_t\left(\sum_{j=1}^{\infty}\rho^j r_{t+j}\right) + \varepsilon_t \\ &\approx CF_t - ER_t \end{aligned} \tag{4}$$

where, $\Delta E_t(\cdot)$ represents the change of the expectation of a certain stochastic variable from time (t-1) to t; e_t expresses the natural logarithmic book return on equity (ROE); r_t is the natural logarithmic return of a stock; ε_t denotes a random approximation error; and ρ is a constant. Following Cohen *et al.* (2002), this paper further defines $CF_t = \Delta E_t\left(\sum_{j=0}^{\infty}\rho^j e_{t+j}\right) + \varepsilon_t$ and $ER_t = \Delta E_t\left(\sum_{j=1}^{\infty}\rho^j r_{t+j}\right)$ as the component of cash flow news and the expected return news at time t, respectively. According to Equation (4), the dependent variable (the unexpected stock return at time t) increases as the expected-return $E_{t-1}\left(r_t\right)$ decreases (i.e. as the expected future ROE increases). The unexpected return equals cash flow news CF_t when the expected return remains constant. In this study, both the stock return and the market-adjusted stock return satisfy the return decomposition. In order for the market-adjusted stock return to meet these requirements, this paper removes the market stock return from the stock return to make the market adjustment.

3.3 The PVAR methodology

To construct the news in Equation (4), this paper requires a forecasting model for stock returns. Following Cohen *et al.* (2002), this paper adopts a panel vector autoregressive (PVAR) system as the forecasting model and the basis for the return decomposition. A typical PVAR model can be constructed as follows:

$$Z_{i,t} = C + \Gamma Z_{i,t-1} + u_{i,t},\ i = 1,\cdots n;\ t = 1\cdots T \tag{5}$$

where C represents a vector of constants; Γ is a 4×4 matrix of coefficients; and $z_{i,t}$ stands for a vector of variables including the logarithmic total return, ROE, book-to-market ratio (BM), and the institutional ownership. According to Cohen *et al*. (2002), by imposing $e' = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$ (e' is a 1×4 vector) and $\lambda' = e'\rho\Gamma\left(I - \rho\Gamma\right)^{-1}$, we can respectively calculate the cash flow (CF_t) and expected return (ER_t) news as follows:

$$CF_t = \left(e' + \lambda'\right) u_{i,t}$$
$$ER_t = \lambda' u_{i,t}$$

This paper also follows the study by Cohen *et al*. (2002) to adopt a first-order VAR. It estimates the VAR using two alternative methods. The first is the fixed effect estimator, which allows heterogeneous intercept in each cross-sectional unit, but assumes a homogeneous slope. Because the sample has a large T, the fixed effect estimator remains consistent if the assumption of intercepts holds. The second estimator this paper considers is the random coefficient estimator Cohen *et al*. (2002) uses. The random coefficient estimator proves less efficient if the slope homogeneity assumption holds. But it is consistent if the assumption fails.

3.4 Tests for investor overreaction and underreaction

This paper's measurements and tests for the market's reaction to cash flow news are based on the study by Cohen *et al*. (2002). The regression coefficient b in Equation (6) acts as an indicator measuring any reaction to the contemporaneous cash flow news:

$$\tilde{r}_t = a + bCF_t + w_t \tag{6}$$

where $\tilde{r}_t$ indicates the market-adjusted return, and CF_t is the cash flow news. Whenever b is greater than 1, it indicates an overreaction, otherwise it indicates an underreaction[5]. w_t is a random error. Following Cohen *et al*. (2002), we assume that the difference between the expected return news of individual stocks and the market index is a random error, which guarantees that the cash flow news is exogenous.

4. Dataset and variables

[5] For details, readers should refer to Campbell (1991), Vuolteenaho (2002), and Cohen *et al* (2002).

This paper obtains its dataset from the Wind database[6]. Because companies' market values could affect this paper's results, this study separates the market into three segmented samples according to companies' sizes as outlined above: Large-Cap market, SME market, and GE market. The profitability tests for the momentum strategy are carried out at monthly, weekly and daily frequency. Because the highest frequency of the available accounting data is monthly, this paper performs the under-reaction test at the monthly frequency. The profitability tests for the reversal strategy are carried out in the same way, except for performing an overreaction test instead. Endogenous variables used in the monthly forecasting model include the stock returns, the ROE, the BM ratios, and the status of institutional ownership of a company.

Monthly datasets for the Large-Cap market and SME market are set up by recording panel observations from the beginning of 2006 to the end of 2017. Datasets for the GE market are set up by recording panel observations from the middle of 2010 to the end of 2017.[7] Except for the ratios of institutional ownership, all the other variables are in logarithm. This paper further defines a state vector Z, which contains the following market-adjusted variables: the logarithmic stock return denoted by $\tilde{r}$; the logarithmic BM ratio, $\tilde{\theta}$; the logarithmic measure of profitability, $\tilde{e}$; and the ratio of institutional ownership, $\tilde{f}$.

This paper starts the samples of Large-Cap and SME from 2006 because a fundamental institutional change, the share-slit reform, was implemented in the second half of 2005. Before the reform, a large portion of the Chinese A-share stocks were not publicly tradable. The reform greatly increased the number of tradable shares and introduced a structural break in stock pricing in China.

In this study, the raw dataset is processed as follows: First, a trimming procedure is adopted by eliminating observed companies with extreme ROE and BM ratio values. Specifically, this approach requires the minimum value of the BM to be 0 and the ROE to be -100%. Second, this paper eliminates companies

[6] The Wind financial database (http://www.wind.com.cn/) is the largest vendor of professional financial data and information on Chinese stocks, bonds, funds, futures, RMB rates, and the macroeconomy. This study excludes all "ST" stocks. ST is an abbreviation for "special treatment". Starting from April, 1998, stocks marked with ST are publicly trade companies that have been alerted by the China Securities Regulatory Commission for abnormal financial conditions. Specifically, ST companies often encounter large losses for at least three consecutive years.

[7] GE market was set up at the end of 2009.

that have less than 30 observations in any of the four endogenous variables. Third, it uses market-adjusted variables for each stock to exclude a common influence caused by systematic market swings. Specifically, the adjustments are conducted by subtracting a benchmark variable from each company-specific variable (Cohen *et al*, 2002). The market adjustment (for all four variables) is as follows:

$$\tilde{Z} = Z - Z_{market} \tag{7}$$

In Equation (7), $\tilde{Z}$ denotes the vector of the market-adjusted variable ($\tilde{r}$, $\tilde{\theta}$, $\tilde{e}$, or $\tilde{f}$); Z denotes the vector of original company-specific variables; and Z_{market} denotes the vector of benchmark variables. After the market adjustment as in Equation (7), the regression coefficient of the realized market-adjusted stock returns on the contemporaneous measurement of market-adjusted cash flow news (shown by Equation (6)) acts as an indicator. Whenever this coefficient is greater than 1, it indicates an overreaction, otherwise it is an underreaction.

Summary statistics are listed in Table 1. Statistical properties for the segmented samples, Large-Cap, SME, and GE market are shown. Panel A of Table 1 shows the mean return in the Large-Cap market is positive. However, the mean return is negative at the monthly frequency for the SME and GE markets. Panel B also shows some differences in the contemporaneous correlations between market-adjusted variables in the three markets. Panel C reports (serial) correlations of the first order of market-adjusted variables. From Panel C, one can see that the market-adjusted returns in all the samples have a negative autocorrelation at the monthly frequency. This indicates that a high return in the past does not necessarily lead to a high return in the future. Panel D presents the statistical description for daily and weekly returns in the three markets.

Table 1: Descriptive statistics

Panel A reports means, standard deviations, minima and maxima of the logarithmic stock return (r); the logarithmic ROE (e), the logarithmic BM ratios (θ); the fractions of institutional ownership (f) for the monthly data. The contemporaneous correlations of monthly market adjusted variables is shown in Panel B. Panel C presents the first-order (serial) correlations of monthly market adjusted variables. Panel D shows the descriptive statistics for daily stock returns and weekly stock returns. In large-cap stock market and small and medium-sized enterprise market, the dataset spans between 2006 and 2017 (144 months). In the growth enterprise market, the dataset spans between 2010 and 2017 (99 months).

	Large-Cap stock market				**SME stock market**				**GE stock market**			
Panel A Descriptive Statistics for monthly data												
Var.	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**
r	0.004	0.154	-1.804	1.907	-0.008	0.170	-1.596	1.335	-0.012	0.198	-1.745	1.906
e	2.756	0.102	-6.907	3.227	1.691	0.202	-6.908	2.368	1.227	0.260	-6.908	2.181
θ	-1.168	0.590	-3.173	0.233	-1.413	0.581	-3.492	-0.097	-1.639	0.629	-3.750	-0.229
f	0.392	0.231	0	0.987	0.313	0.237	0	0.996	0.247	0.194	0	0.992
Panel B: Contemporaneous correlations for monthly data												
Var.	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$
$\tilde{r}_t$	1	0.010	-0.096	0.033	1	0.012	-0.093	0.039	1	-0.002	-0.103	0.018
$\tilde{e}_t$	0.010	1	-0.122	0.100	0.012	1	-0.158	0.117	-0.002	1	-0.227	0.092
$\tilde{\theta}_t$	-0.096	-0.122	1	0.149	-0.093	-0.158	1	-0.092	-0.103	-0.227	1	-0.095
$\tilde{f}_t$	0.033	0.100	0.149	1	0.039	0.117	-0.092	1	0.018	0.092	-0.095	1
Panel C: First-order (serial) correlations for monthly data												
Var.	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$	$\tilde{r}_t$	$\tilde{e}_t$	$\tilde{\theta}_t$	$\tilde{f}_t$
$\tilde{r}_{t-1}$	-0.057	0.014	-0.093	0.031	-0.067	0.013	-0.081	0.038	-0.083	-0.0001	-0.089	0.018
$\tilde{e}_{t-1}$	0.016	0.772	-0.119	0.104	0.017	0.786	-0.165	0.114	0.006	0.776	-0.234	0.094
$\tilde{\theta}_{t-1}$	0.082	-0.119	0.969	0.157	0.064	-0.152	0.943	-0.084	0.060	-0.227	0.935	-0.088
$\tilde{f}_{t-1}$	0.027	0.098	0.144	0.970	0.034	0.116	-0.099	0.972	0.014	0.090	-0.094	0.957
Panel D: Descriptive Statistics for daily and weekly data												
Var	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**
r_{daily}	0.0002	0.033	-1.293	1.068	-0.0004	0.038	-1.447	0.146	-0.0005	0.043	-1.455	0.097
r_{weekly}	0.001	0.074	-1.500	1.009	-0.002	0.084	-1.562	0.478	-0.003	0.096	-1.470	0.477

5. Empirical results

This study obtains the average returns of momentum strategies and the corresponding t-statistics by using the methodology as described in the above sections. It sorts stocks in an ascending order in terms of the overall performance of returns over the past J periods. According to the ranking, the top n stocks are chosen as the loser portfolios, and the bottom n stocks are chosen as the winner portfolios. In the Large-Cap stock market, the value of n is set to 80. In the SME stock markets, the value of n is set to 50. In the GE stock market, the value of n is set to 30. This ensures the size of each portfolio is approximately 10% of the sample. In every portfolio, the stocks are equally weighted.

Table 2 reports the average monthly returns and the t statistic of momentum strategies in different markets, where Panel A, Panel B, and Panel C respectively present the results in the Large-Cap, SME and GE stock markets. For every J/K strategy, the values in the first column correspond to the values of J (the length of period to form the portfolio). The values in the first row indicate the values of K (the holding period of the portfolio). According to the results in Table 2, in all three markets, monthly momentum strategies fail. All 16 strategies in each market realize negative returns, and the t values suggest high significance. Specifically, Table 2 indicates that strategies that involve buying winners and selling losers fail. However, to the contrary, there are clearly return reversal effects at the monthly frequency.

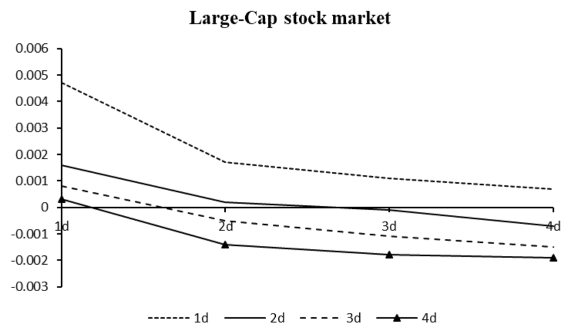
Table 2: Returns of monthly momentum strategies portfolios

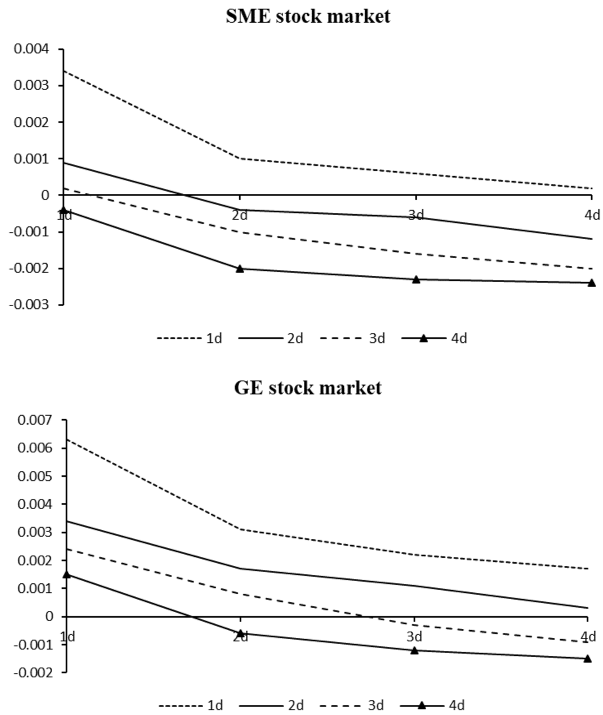
This table reports the average return and t statistic of total 16 momentum strategies. The value of J in the first column indicates that the portfolios are formed according to the past J months' return. The value of K in the first row indicates that the portfolios will be held for K months. The value in the brackets is the t statistic of the J/K strategies. The period of the sample ranges from January of 2006 to the December of 2017 (144 months). In the Growth Enterprise market, the dataset spans between 2010 and 2017 (90 months). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Strategies (J/K)	K=1	K=3	K=6	K=9
Panel A: Large-Cap stock market				
J=1	-0.0224***	-0.0153***	-0.0098***	-0.0071***
	(-4.9356)	(-6.6863)	(-6.6924)	(-6.2241)
J=3	-0.0294***	-0.0218***	-0.0140***	-0.0108***
	(-6.2121)	(-8.3027)	(-8.4826)	(-8.2146)
J=6	-0.0271***	-0.0216***	-0.0151***	-0.0122***
	(-6.0284)	(-8.7313)	(-9.3354)	(-9.0623)
J=9	-0.0253***	-0.0210***	-0.0150***	-0.0130 ***
	(-6.1771)	(-9.0235)	(-9.0901)	(-9.9131)
Panel B: SME stock market				
J=1	-0.0277***	-0.0180***	-0.0109***	-0.0088***
	(-8.6360)	(-8.8202)	(-7.7887)	(-8.0483)
J=3	-0.0328***	-0.0230***	-0.0155***	-0.0140***
	(-7.7011)	(-8.7575)	(-9.3205)	(-10.9136)
J=6	-0.0290***	-0.0227***	-0.0182***	-0.0166***
	(-6.6635)	(-9.1517)	(-11.8488)	(-13.7919)
J=9	-0.0270***	-0.0249***	-0.02048***	-0.0176***
	(-6.4138)	(-10.2170)	(-13.1976)	(-14.5039)
Panel C: GE stock market				
J=1	-0.0396***	-0.0277***	-0.0171***	-0.0146***
	(-6.7402)	(-7.4459)	(-7.2615)	(-8.8880)
J=3	-0.0494***	-0.0393***	-0.0268***	-0.0241***
	(-6.3945)	(-8.9776)	(-9.4712)	(-10.7524)
J=6	-0.0508***	-0.0425***	-0.0330***	-0.0277***
	(-5.5544)	(-7.8175)	(-9.5630)	(-10.9209)
J=9	-0.0552***	-0.0447***	-0.0327***	-0.0288***
	(-5.7335)	(-8.1471)	(-9.4043)	(-12.2770)

After investigating the monthly momentum strategies, this study conducts the test for weekly and daily momentum strategies. Table 3 reports the average weekly returns and the t statistic of momentum strategies in different markets. According to the results in Table 3, in all three markets, weekly momentum strategies fail. Instead, all weekly reversal strategies, which buy past loser stocks and sell past winner stocks, generate positive returns.

The results from daily data are mixed. Based on the results in Table 4, in all three markets, momentum strategies with a shorter formation period (one day) are profitable. With formation periods of fewer than four days, all momentum strategies that have a holding period of one day are also profitable. However, daily momentum strategies with longer formation periods and holding periods suffer losses. These losses are profits for reversal strategies with the same formation periods and holding periods. Figure 1 plots the daily momentum strategy return. The numbers on the vertical axis are the daily returns. The horizontal axis indicates the lengths of holding periods. Different types of the lines illustrate four different formation periods (with the dotted lines standing for a one-day formation period, solid lines for a two-day formation period, broken lines for a three-day formation period, and the triangle-marked lines for 4-day formation period). Figure 1 clearly suggests that, for a given holding period, the daily momentum strategy return declines as the formation period increases from one day to four days. The daily momentum return also declines as the holding period increases from one day to four days for a given formation period.





Note: This figure plots daily returns along different momentum strategies. The vertical axis is the daily return while the horizontal axis indicates the lengths of holding periods. Different types of the lines illustrate momentum return patterns based upon four different formation periods (with the dotted lines standing for 1-day formation period, solid lines for 2-day formation period, broken lines for 3-day formation period, and the triangle-marked lines for 4-day formation period).

Figure 1: Daily momentum returns and investment horizons

Therefore, momentum strategies are most profitable over the shortest horizons. Over longer horizons, they suffer losses. Instead, the reversal strategies are profitable over longer horizons. Previous literature finds that in the US, the momentum strategies work for horizons of less than one year, while reversal strategies work for horizons beyond one year. Our results suggest that the horizons over which momentum strategies are profitable are much shorter in China than in the US. Previous literature suggests that because of behavioral biases, individual investors underreact to company cash flow news. Therefore, future stock prices have to further increase (decrease) to match the changes in fundamental values caused by good (bad) news. This explains why momentum strategies which assume that past price trends will continue are profitable. However, if Chinese and US individual investors face the same behavioral biases, the horizons over which the momentum strategies make profits should be the same. The differences in the empirical results are caused by the differences in the institutional environments between China and the US. In China, there are more individual investors, as a result, stock price bubbles can last longer and grow larger. Rational institutional arbitragers can make profits by riding the bubble rather than attempting to correct the mispricing. However, as the bubble size grows, these arbitragers become more sensitive to news events. This is because news events about company cash flows can not only confirm their belief about the size of the bubble but also coordinate all arbitragers' belief so that a speculative attack on the overpriced stock can be successful. In other words, larger bubble sizes in China suggest that price movements triggered by news events are much larger than in the US. Therefore, Chinese institutional arbitragers react more strongly to cash flow news than US institutional arbitragers. As a result, although individual investors underreact to cash flow news, stock returns can still overreact to cash flow news due to the overreaction of institutional investors.

Table 3: Returns of weekly momentum strategies portfolios

This table reports the average return and t statistic of 16 momentum strategies. The value of J in the first column indicates that the portfolios are formed according to the past J weeks' return. The value of K in the first row indicates that the portfolios will be held for K weeks. The value in the brackets is the t statistic of the J/K strategies. The period of the sample ranges from January of 2006 to the December of 2017 (611 weeks). In the Growth Enterprise market, the dataset spans between 2010 and 2017 (385 weeks). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Strategies (J/K)	K=1	K=2	K=3	K=4
Panel A: Large-Cap stock market				
J=1	-0.0090***	-0.0046***	-0.0033***	-0.0033***
	(-7.4018)	(-6.0069)	(-5.7051)	(-6.8893)
J=2	-0.0064***	-0.0037***	-0.0035***	-0.0040***
	(-5.2407)	(-4.7502)	(-5.8798)	(-7.8512)
J=3	-0.0056***	-0.0043***	-0.0046***	-0.0051***
	(-4.4949)	(-5.4059)	(-7.3233)	(-9.0055)
J=4	-0.0071***	-0.0058***	-0.0059***	-0.0061***
	(-5.6309)	(-7.2492)	(-8.9917)	(-10.3850)
Panel B: SME stock market				
J=1	-0.0099***	-0.0062***	-0.0049***	-0.0044***
	(-9.4495)	(-9.1987)	(-9.6969)	(-9.9923)
J=2	-0.0089***	-0.0063***	-0.0055***	-0.0053***
	(-8.6097)	(-9.6343)	(-11.1233)	(-11.9551)
J=3	-0.0080***	-0.0063***	-0.0059***	-0.0060***
	(-7.4997)	(-9.2802)	(-10.9990)	(-12.1196)
J=4	-0.0084***	-0.0074***	-0.0072***	-0.0071***
	(-8.1614)	(-10.7711)	(-12.7715)	(-13.5716)
Panel C: GE stock market				
J=1	-0.0055***	-0.0046***	-0.0045***	-0.0044***
	(-2.6848)	(-3.5644)	(-4.5493)	(-5.3180)
J=2	-0.0079***	-0.0072***	-0.0071***	-0.0074***
	(-4.2026)	(-6.0729)	(-7.3724)	(-9.0815)
J=3	-0.0104***	-0.0098***	-0.0094***	-0.0092***
	(-5.6902)	(-8.0815)	(-9.4937)	(-11.1634)
J=4	-0.0110***	-0.0103***	-0.0101***	-0.0101***
	(-6.2510)	(-8.7600)	(-10.8390)	(-12.3502)

Table 4: Returns of daily momentum strategies portfolios

This table reports the daily average return and t statistic of total 16 momentum strategies. The value of J in the first column indicates that the portfolios are formed according to the past J trading days' return. The value of K in the first row indicates that the portfolios will be held for K trading days. The value in the brackets is the t statistic of the J/K strategies. The period of the sample ranges from January of 2006 to the December of 2017 (2,917 days). In the Growth Enterprise market, the dataset spans from the July of 2010 to the December of 2017 (1,826 days). ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A:				
Strategies (J/K)	**K=1**	**K=2**	**K=3**	**K=4**
J=1	0.0047***	0.0017***	0.0011***	0.0007***
	(18.7093)	(9.6059)	(7.9683)	(5.6179)
J=2	0.0016***	0.0002	-0.0001	-0.0007***
	(6.4958)	(0.9847)	(-0.6398)	(-5.8988)
J=3	0.0008***	-0.0005***	-0.0011***	-0.0015***
	(3.3445)	(-2.7236)	(-7.9755)	(-12.9755)
J=4	0.0003	-0.0014***	-0.0018***	-0.0019***
	(1.1354)	(-7.7816)	(-12.7422)	(-16.3747)
Panel B: SME stock market				
J=1	0.0034***	0.0010***	0.0006***	0.0002**
	(14.2995)	(5.9675)	(4.5378)	(2.2095)
J=2	0.0009***	-0.0004**	-0.0006***	-0.0012***
	(3.8664)	(-2.4179)	(-4.7462)	(-10.4823)
J=3	0.0002	-0.0010***	-0.0016***	-0.0020***
	(0.7130)	(-6.5397)	(-13.1515)	(-18.2940)
J=4	-0.0004*	-0.0020***	-0.0023***	-0.0024***
	(-1.8462)	(-12.2494)	(-18.2202)	(-21.5232)
Panel C: GE stock market				
J=1	0.0063***	0.0031***	0.0022***	0.0017***
	(15.0665)	(10.0547)	(8.4541)	(7.2043)
J=2	0.0034***	0.0017***	0.0011***	0.0003
	(8.2417)	(5.4397)	(4.2058)	(1.1581)
J=3	0.0024***	0.0008***	-0.0003	-0.0009***
	(6.0414)	(2.6097)	(-1.2081)	（-4.0376)
J=4	0.0015***	-0.0006*	-0.0012***	-0.0015***
	(3.7328)	(-1.8701)	(-4.8703)	(-7.1789)

Among all types of news, listed companies' cash flow news relates most directly to the fundamental value of the stocks. Moreover, the cash flow news is publicly observable at the monthly frequency in China. To further investigate the underlying reason why monthly momentum strategies are not profitable, this study tests whether stock returns overreact to company cash flow news in China. The estimation results of the fixed effect models are reported in Table 5.

Table 5: Estimates for the first-order marketed-adjusted PVAR model using the fixed effect model

PVAR models are implemented in three segmented markets: the Large-Cap, SME and GE stock markets. Each row of numbers represents estimates of coefficients and the corresponding t statistic. All coefficients are estimated in the fixed effect model. The $\tilde{r}_t$ represents logarithmic stock returns; $\tilde{e}_t$ represents logarithmic book-to-market ratios; $\tilde{\theta}_t$ represents logarithmic returns on equity; and $\tilde{f}_t$ represents fractions of shares outstanding owned by institutions. All the variables in the model are market-adjusted variables. The value in the parentheses is the t statistic. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Large-Cap stock market				**SME stock market**				**GE stock market**			
	Coefficients using fix effect model (the matrix):											
	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$
$\tilde{r}_t$	-0.047***	0.045***	0.030***	0.011***	-0.061***	0.023***	0.033***	0.044***	-0.077***	0.011**	0.027***	0.027***
	(-15.710)	(10.738)	(34.084)	(4.551)	(-13.358)	(5.813)	(19.326)	(10.970)	(-11.671)	(1.960)	(10.349)	(3.488)
$\tilde{e}_t$	0.002	0.777***	-0.006***	0.005***	0.001	0.747***	-0.011***	0.018***	-0.003	0.711***	-0.017***	0.013*
	(1.230)	(359.237)	(-13.805)	(4.055)	(0.283)	(222.615)	(-7.835)	(5.467)	(-0.507)	(146.983)	(-7.521)	(1.892)
$\tilde{\theta}_t$	-0.006**	0.006	0.943***	-0.003	0.015***	-0.044***	0.882***	-0.064***	0.013*	-0.039***	0.868***	-0.053***
	(-1.975)	(1.340)	(945.617)	(-1.221)	(2.884)	(-9.860)	(447.338)	(-13.820)	(1.764)	(-6.408)	(302.584)	(-6.118)
$\tilde{f}_t$	0.005***	0.005***	0.009***	0.937***	0.005***	0.003*	0.001*	0.937***	0.002	0.0008	-0.002*	0.915***
	(4.057)	(2.766)	(23.811)	(887.902)	(2.781)	(1.839)	(1.721)	(572.579)	(0.966)	(0.434)	(-1.725)	(333.318)

In Table 5, we observe that the regression coefficients on the last month's returns are significantly negative in the return equation (as shown in the fourth row in Table 5) across all market segments using a fixed effect model. This observation indicates the existence of reversal behavior. This is consistent with the results of unprofitable momentum strategies. This paper then investigates the responses of the returns to cash flow news. The results are listed in Table 6. Under a fixed effect model, Table 6 suggests that the regression coefficients of the market-adjusted return ($\tilde{r}_t$) on cash flow news (CF_t) is larger than 1 and is statistically significant. This means that across all the market segments (the Large-Cap, SME, and GE stock markets), a significant overreaction to cash flow news is always present, and the overreaction implies potential profits for reversal strategies.

Table 6: Regressions and tests using the fixed effect model

This table reports regression results and tests using a fixed effect model across the three market segments: the Large-Cap, SME and GE stock markets. The third row of the table presents the regression coefficients of the market-adjusted return (the dependent variable) on the cash flow news (the independent variable). F-tests are also reported. The value in the parentheses is the t statistic. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Large-Cap stock market	**SME stock market**	**GE stock market**
	CF_t	CF_t	CF_t
$\tilde{r}_t$	1.242*** (797.266)	1.092*** (681.136)	1.116*** (698.929)
F-Test p values	0.000	0.000	0.000

As a robustness test, this paper also implements a random coefficient model to re-run all the above tests. In Table 7, the random coefficient model has very similar results as shown by the fixed effect model. From Table 8, we can also find that the regression coefficients of the market-adjusted stock returns on the cash flow news do not change significantly compared to the stated results in the fixed effect model.

Table 7: Estimates for the first-order marketed-adjusted PVAR model using the random coefficient model

PVAR models are implemented in three segmented markets: Large-Cap, SME and GE stock markets. Each row of numbers represents estimates of coefficients and the corresponding t statistic. All coefficients are estimated in the random coefficient models. The $\tilde{r}_t$ represents logarithmic stock returns; $\tilde{e}_t$ represents logarithmic book-to-market ratios; $\tilde{\theta}_t$ represents logarithmic returns on equity; and $\tilde{f}_t$ represents fractions of shares outstanding owned by institutions. All the variables in the model are market-adjusted variables. The value in the parentheses is the t statistic. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Large-Cap stock market				SME stock market				GE market			
	Coefficients using random coefficient model (the matrix):											
	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$	$\tilde{r}_{t-1}$	$\tilde{e}_{t-1}$	$\tilde{\theta}_{t-1}$	$\tilde{f}_{t-1}$
$\tilde{r}_t$	-0.049***	0.127***	0.053***	0.007	-0.071***	0.063***	0.044***	0.042***	-0.084***	0.014	0.040***	0.024
	(-10.023)	(4.782)	(18.268)	(0.895)	(-10.199)	(3.371)	(10.661)	(4.478)	(-8.713)	(0.798)	(5.996)	(1.014)
$\tilde{e}_t$	0.001	0.725***	-0.005***	0.002	-0.004	0.745***	-0.006	0.014**	-0.003	0.741***	-0.010***	-0.003
	(0.789)	(180.537)	(-8.031)	(1.203)	(-0.676)	(131.024)	(-1.531)	(2.408)	(-0.466)	(97.847)	(-2.821)	(-0.210)
$\tilde{\theta}_t$	-0.011**	-0.062*	0.905***	-0.003	0.009	-0.144***	0.844***	-0.055***	0.002	-0.067***	0.832***	-0.054**
	(-2.129)	(-1.895)	(246.813)	(-0.407)	(1.135)	(-6.999)	(155.853)	(-4.450)	(0.168)	(-3.901)	(107.159)	(-2.137)
$\tilde{f}_t$	0.007***	0.021*	0.011***	0.925***	0.005*	0.008	0.003	0.925***	0.001	0.002	0.001	0.890***
	(3.047)	(1.867)	(8.105)	(313.660)	(1.757)	(1.271)	(1.478)	(249.486)	(0.425)	(0.315)	(0.493)	(137.537)

Table 8: Regressions and tests using the random coefficient model

This table reports regression results and tests using a random coefficient model across the three market segments: the Large-Cap, SME and GE stock markets. The third row of the table presents the regression coefficients of the market-adjusted return (the dependent variable) on the cash flow news (the independent variable). F-tests are also reported. The value in the parentheses is the t statistic. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Large-Cap stock market	**SME stock market**	**GE stock market**
	CF_t	CF_t	CF_t
$\tilde{r}_t$	1.203*** (588.293)	1.097*** (625.753)	1.127*** (559.354)
F-Test p values	0.000	0.000	0.000

The above results provide evidence that significant and robust reversal behavior exists in the Chinese A-share stock market at the monthly frequency. It is also evident that overreaction drives this reversal behavior. Compared to the US stock market, where underreaction prevails, the Chinese A-share stock market shows the opposite.

6. Conclusion

This study investigates the profitability of momentum and reversal strategies of different investment horizons in the Chinese stock market. We find that in the Chinese stock market, where the proportion of individual investors is much higher than that in the US, the horizons over which momentum strategies make profits are much shorter than those in the US. While in the US stock market, momentum strategies make profits over horizons as long as one year, they only work for horizons less than one week in China. We show that this is because investors are generally overreact to the company cash flow news in China while underreact to cash flow news in the US. We argue this is because the high proportion of individual investors in China. Individual investors make price wildly deviate from company fundamental values. As a result, rational institutional investors who try to profit by either riding the bubble or correcting the mispricing are more sensitive to news on company cash flows. For longer investment horizons, reversal strategies are profitable.

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Appendix

Table A1: Distribution of investors' positions at the end of 2015 (in RMB)

Position ranges of the non-restricted and negotiable A-share stocks (End of Year, RMB)	Individual (retail) investors		Professional institutional i nvestors		Total	
	Number of Investors	Weight %	Number of Investors	Weight %	Number of Investors	Weight %
a. Less than 10 thousand	11,612,075	23.15	4,026	6.15	11,616,101	23.12
b. 10-100 thousand	24,323,556	48.48	8,028	12.26	24,331,584	48.44
c. 100-500 thousand	10,860,279	21.65	10,806	16.50	10,871,085	21.64
d. 0.5-1 million	1,881,845	3.75	5,752	8.78	1,887,597	3.76
e. 1-5 million	1,315,609	2.62	11,864	18.11	1,327,473	2.64
f. 5-10 million	109,951	0.22	4,389	6.70	114,340	0.23
g. 10-100 million	60,207	0.12	11,711	17.88	71,918	0.14
h. More than 100 million	4,417	0.01	8,931	13.63	13,348	0.03
Total	50,167,939	100.00	65,507	100.00	50,233,446	100.00