International Journal of Multiphysics
Volume 18, No. 3, 2024
ISSN: 1750-9548

Research on Pricing Power of Fama-French Five-factor Model Combined with Trend Factor

Yanwei Hao, Feiran Dong*
Shandong University (Weihai), Weihai, China
*Corresponding Author.

Abstract

Technical analyses are popular in investment practice in the Chinese stock market. However, with the in-depth study of technical indicators, trend strategies constructed based on a single window period have been proven to be highly volatile in terms of returns. And also, there is a wide range of academic views on the implementation of trend strategies to achieve excess returns in the Chinese market. Based on these, this paper constructs a trend factor using a moving average model, employs Chinese A-share data from 2010-2023 to verify the effectiveness of the trend factor for single-factor stock selection in the Chinese stock market through empirical analyses, respectively, and combines the trend factor with a traditional asset pricing model to validate the feasibility of the improved Fama-French five-factor model stock selection strategy by adding the trend factor and the pricing ability of the model, and the robustness of the findings is confirmed by robustness tests. The conclusions of the study provide targeted recommendations for individual and institutional investors and have certain theoretical and practical significance.

Keywords: Trend factor, technical analysis, Fama-French five-factor model, asset pricing.

1. Introduction

Since the 1990s, China's stock market has experienced significant growth and development. The proliferation of listed companies and the leap in information technology have combined to facilitate the emergence of massive amounts of information, providing investors with a wealth of material for analysis. However, information overload also brings the challenge of "information flood", affecting investors' judgement and decision-making. Therefore, in the information age, mining and processing effective information in the stock market to guide the formulation of investment strategies has become an urgent problem. As the most direct and least contaminated source of public information in the stock market, stock price carries a wealth of market information. Technical analysis, which is essentially an investment decision-making method that predicts future performance through the past price trends of stocks, has long attracted much attention in both academic and practical circles. Given the large number of retail investors and the highly speculative nature of the Chinese stock market, technical analysis, especially the trend factor, is widely used. The trend factor, through the comprehensive information of different window periods, provides a method for achieving continuous and stable returns. Incorporating trend factors into the framework of classical asset pricing models is of far-reaching significance in revealing the pricing laws of the Chinese stock market.

The issue of whether excess returns can be obtained by analysing stock price trends has always been controversial in theoretical studies. Traditional finance scholars who support the efficient market hypothesis argue that the future value of stocks is sufficiently expressed in their prices and therefore no excess profits can be made by studying stock price trends[1]. However, the reality is that stock price trends are still one of the most persistent and strongest anomalies, so the efficient market theory began to reject the efficient market hypothesis, and through models such as BSV, DHS, and HS[2-4] the irrational root causes of investor decision-making were revealed, which provided a theoretical basis for technical analysis.The study by Han et al. (2016) further confirmed the the excess return potential of the trend factor in the U.S. market[5].

Therefore, this paper integrates the trend factor into the traditional asset pricing model, and uses the research methods of these mature systems to analyze the performance of the price trend factor in the Chinese stock market, in an attempt to theoretically illustrate the predictive role of the historical stock price on future returns, to provide theoretical support for the effectiveness of technical analysis in the Chinese stock market, and to open new paths for discovering asset pricing theories that are more in line with the characteristics of the Chinese stock market. Meanwhile, the findings of this paper also provide new ideas for investors to pursue higher returns under the given risks.

2. Empirical Tests of the Validity of Trend Factors

2.1 Data sources

This paper takes the A-share listed companies in Shanghai and Shenzhen from January 2010 to July 2023 as the research sample, in order to avoid outliers have been excluded from the financial industry and ST status stocks, the data used in this paper are all from the CSMAR database. Since the calculation of trend factor requires the maximum span of the mean index to be 235 days and the mean value of the regression coefficient needs to be calculated for 52 weeks, the actual effective sample interval of this paper is from 2012 to 2023, with a total of 604 weeks of data.

2.2 Trend factor construction

Based on the moving average model proposed by Zhu and Zhou (2009)[6] and the theoretical proof of Han (2011)[7] for the predictive ability of averaging indicators on the future returns of assets, Han et al.(2016)[1] constructed a trend factor by combining the moving average prices of different periods in order to capture the short-, medium-, and long-term price signals of the stock market simultaneously. Due to the high volatility of daily data, the existing trend factors are mainly constructed based on monthly and weekly data. However, studies based on monthly data do not have a strong explanation of future stock returns. For the choice of data period, Yuan (2022)[8] found that the trend factor constructed using weekly data is able to achieve a weekly return of 1.21%, which is statistically significant and remains very robust using different tests, and outperforms the monthly trend factor return. Therefore, this paper refers to its approach to construct a weekly trend factor in the following steps:

Firstly, on the last trading day of each week *t*, the moving average price is calculated for a given period. The resulting moving average price of the stock on the last trading day of week *t* for a different window L $A_{it,L}$ is obtained as in equation (1):

$$A_{it,L} = \frac{P^t_{i,d-L+1} + P^t_{i,d-L+2} + \ldots + P^t_{i,d-1} + P^t_{i,d}}{L} \tag{1}$$

Where $P^t_{i,d}$ is the price of the stock i (the weekly closing price of the stock) at d on the last trading day of the week t ; and L is the moving period for the moving average.

There are three steps in the process of forecasting future cross-sectional returns using the moving average indicator. In the first step, the weekly closing price of the stock $P^t_{i,d}$ is used to price normalise the moving average price $A_{it,L}$ for the different windows in equation (1) and the resulting normalised moving average price $\tilde{A}_{it,L}$ is shown in equation (2):

$$\tilde{A}_{it,L} = \frac{A_{it,L}}{P_{id}^{i}} \tag{2}$$

In the second step, at each weekly t, the standardised moving average price $\tilde{A}_{it-1,L_j}$ of the $t-1$ week is regressed on the week's stock return $r_{i,t}$ using the regression equation in equation (3):

$$r_{i,t} = \beta_{0,t} + \sum_{j} \beta_{j,t} \tilde{A}_{it-1,L_j} + \varepsilon_{i,t}, i = 1, \cdots, n \tag{3}$$

Where $r_{i,t}$ is the weekly return of the stock i in week t, $\tilde{A}_{it-1,L_j}$ is the moving average price of the stock i on the last trading day of week $t-1$ for the period L_j, and the values of j are chosen to be 3, 7, 10, 20, 60, 100, and 235 days, which combines the different time windows of the short-term, medium-term, and long-term. $\beta_{j,t}$ is the regression coefficient of the moving average price of j for different windows $\tilde{A}_{it-1,L_j}$ on weekly returns in week t, $\beta_{0,t}$ is the intercept of the regression on weekly returns in week t, n is the number of stocks in the market, and $\varepsilon_{i,t}$ is the residual term.

In the third step, the expected stock returns for the coming week are forecasted using past moving average price regression coefficients, calculated as in equation (4):

$$E_t\left[r_{i,t+1}\right] = \sum_{j} E_t\left[\beta_{j,t+1}\right] \tilde{A}_{it,L_j} \tag{4}$$

Where $E_t\left[r_{j,t+1}\right]$ is the expected return of the stock i at cycle $t+1$, $E_t\left[\beta_{j,t+1}\right]$ is the estimate of the moving average price coefficient for the cycle L_j, $E_t\left[\beta_{j,t+1}\right]$ is the average of the moving average price coefficients for the last 52 weeks from cycle t, and $E_t\left[\beta_{j,t+1}\right]$ is calculated as in equation (5):

$$E_t\left[\beta_{j,t+1}\right] = \frac{1}{52} \sum_{m=1}^{52} \beta_{j,t+1-m} \tag{5}$$

As can be seen from the above equation, all of the information used in forecasting future stock returns $E_t\left[r_{j,t+1}\right]$ using the trend factor is derived from historical information from the first t week and earlier. The reason for choosing a rolling period of 52 weeks is that 52 weeks contains about a year's worth of information about a stock, which is enough to form a clear trend without including useless information that is out of date due to the long period.

As a result of the above calculations, the estimate of the weekly cross-section returns at week $t+1$ predicted using the information from the moving average price of the period prior to week t $E_t\left[\beta_{j,t+1}\right]$ is the trend factor to be constructed in this paper.

2.3 Descriptive statistics

This paper uses portfolio analysis in order to study the performance of each stock selection factor[7,9,10] . The study sorts the research sample based on the magnitude of the trend factors calculated in the previous paper and divides it into ten groups, each containing stocks with similar trend factors. It then constructs ten investment portfolios, each consisting of stocks from one of the groups, and weights them equally. The difference between the portfolio with the highest trend factor and the one with the lowest trend factor is then taken as the return on the trend factor. After holding the combination for a week, it is balanced again in the next week, resulting in a time series of trend factor returns over 604 weeks, as well as a series of returns for each of the ten groups. Finally, the serial correlation of the trend factor's return and the monotonicity between the groups are tested.

Figure 1 reports the weekly average returns of decile portfolios sorted by trend factors, where the horizontal axis represents the decile portfolio and the vertical axis represents the weekly average return of the investment portfolio. As can be seen from the figure, the highest return among the decile groups is the Trend1 group with the largest value of the trend factor, whose average weekly return is up to 0.40%, while the lowest return is the Trend10 group with the smallest value of the trend factor, whose average weekly return is only -0.24%, and the long/short portfolio return is as high as 0.64%, which is a very strong profitability of the factor. At the same time, the subgroups return from the factor largest group to the most small group shows a very obvious decreasing trend, factor monotonicity is also very strong. So far, this paper initially from the long-short portfolio returns and factor monotonicity two aspects of the proof of the trend factor has a very strong profitability.

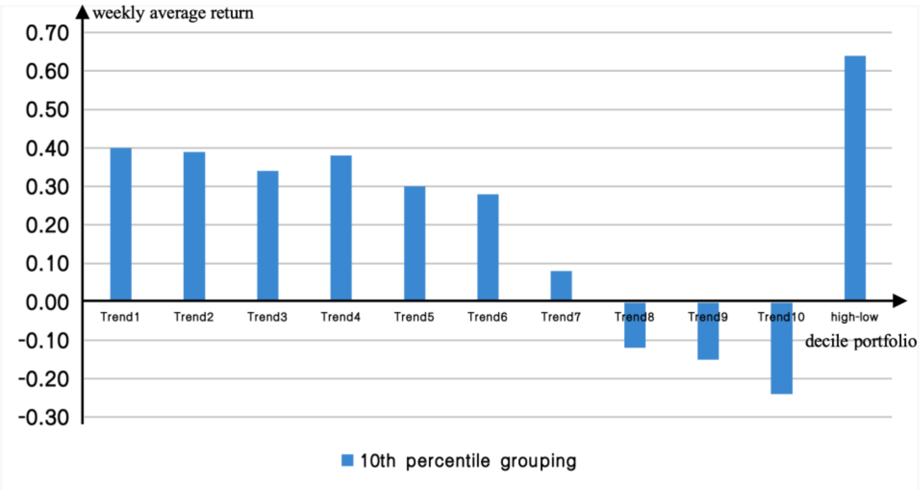

Figure 1 Trend factor weekly average returns

The original purpose of this paper's study of the trend factor lies in the factor's ability to capture price information across different investment horizons in order to obtain higher returns than those obtained by the classical volume factor constructed on a single investment horizon. Therefore, this paper constructs other volume price factors for three investment horizons, short-term, medium-term, and long-term, at weekly frequencies and compares them with the returns of the trend factor. Among them, SREV(1,1) refers to the short-term reversal factor with a formation period of 1 week and a holding period of 1 week; MOM(6,6) refers to the medium-term momentum factor with a formation period of 6 weeks and a holding period of 6 weeks; and LREV(26,26) refers to the long-term reversal factor with a formation period of 26 weeks and a holding period of 26 weeks. Take the SREV(1,1) factor as an example, with reference to Qi and Wang (2015) [11], the specific practice of factor construction is as follows: to decile as a node, the last week's returns of the stocks in the market are sorted, and ten portfolios are constructed in each subgroup according to the weighting of the equal weights of each stock per group of equally weighted portfolios, respectively. Established studies have attempted to explain the reasons for the trend effect from the perspective of lottery investors[12], turnover[13], market structure[14] and analyst attention[15].As the trend effect that dominates under different maturities in the Chinese market is inconclusive, this paper goes long on the highest return group and short on the lowest return group, and then balances it after holding it for a week to get the return sequence of the long and short portfolios; if the final average weekly return is positive, it is considered to dominate the momentum effect under the investment tenure; conversely, if the return is negative, it is considered to be dominated by the inversion effect under the tenure. The A comparison of the returns of the Trend factor and the classical volume factor is shown in Table 1. As can be seen from the table, the Trend factor has the highest return, with an average weekly return of 0.641%, which corresponds to the t statistic of 5.93 and is significant at the 1% confidence level. Among the classical quantitative factors, the short-term reversal factor SREV has the highest average weekly return of

0.236%, corresponding to the t statistic of 2.20, which is significant at the 5% confidence level, indicating that it can be assumed that there is a short-term reversal effect in China's stock market, which is consistent with the study of Qu and Liu (2020)[16]. However, the intermediate-term momentum factor MOM and the long-term reversal factor LREV factor do not pass the significance test, which is proved to be different from those of the mature and developed country's stock markets[17-19], and the medium-term momentum factor MOM and long-term reversal factor LREV do not pass the significance test. As far as the empirical results of this paper are concerned, there is no significant medium-term momentum effect and long-term reversal effect in the Chinese stock market. Comparing the average returns of each factor, it can be seen that the return of Trend is much higher than that of the classical volume factor, and compared with the short-term reversal factor SREV, which has the highest return, it is also about 1.7 times higher.

Meanwhile, the standard deviations of the four types of factors are 2.660, 2.640, 1.060, and 1.041, respectively, and the standard deviation of the trend factor Trend is slightly higher than that of the other factors, which suggests that the returns of the trend factor may be more volatile in comparison to the other factors; however, according to the research of Bask and Gencay (1998) [20] , the high standard deviation of the factors may also be derived from the extreme high returns of the trend factor, and thus This paper is not yet in a position to give a conclusion on whether investing with trend factors exposes returns to a higher risk of high risk of loss. On this basis, the paper chooses to continue to compare the returns of the factors on an annual basis to enable further testing.

Table 1 Descriptive statistics.

factor	sample size	Mean (%)	Standard deviation (%)	Minimum (%)	Maximum (%)
Trend	604	0.641*** (5.93)	2.660	-12.487	23.756
SREV (1,1)	604	0.236** (2.20)	2.640	-14.207	23.691
MOM (6,6)	604	0.052 (1.21)	1.060	-16.654	8.570
LREV (26,26)	604	0.014 (0.33)	1.041	-6.282	4.081

Note: *, ** and *** denote statistically significant at the 10%, 5% and 1% confidence levels, respectively.

In Table 2, this paper further considers the annual returns of each volume factor. Comparing the returns of each factor in each year, it can be found that as a technical analysis type of factor, the trend factor is closely linked to the direction of the general market, but it is worth noting that when the overall stock market volatility is relatively large, the trend factor is not worse, but on the contrary, the performance is better. In 2015, for example, the A-share market crashed, but the return of the trend factor was as high as 2.505, which gives the signal that as long as the market trend can be correctly grasped investors can even achieve a high degree of return when the stock market crashes; in contrast, other factors do not have this characteristic. This is consistent with the finding that moving average prices are more predictive of future stock prices in years when stock prices are more volatile.

Table 2 Annual returns by factor.

year	Trend	SREV	MOM	LREV
2012	0.216	0.343	-0.021	0.045
2013	0.341	0.524	0.059	0.052
2014	0.186	0.152	0.156	0.098
2015	2.505	0.514	0.239	-0.008
2016	1.031	0.360	0.043	0.059
2017	0.273	0.005	0.071	-0.082
2018	0.220	-0.250	0.094	0.053
2019	-0.042	0.039	-0.156	-0.167
2020	0.000	-0.117	-0.161	-0.128
2021	0.197	-0.142	-0.020	0.073
2022	0.342	0.135	0.127	0.097
2023	0.270	0.052	0.072	0.068

In Figure 2, the annual return rankings of each factor can be more intuitively observed, where the horizontal axis represents the year from 2012-2023 and the vertical axis represents the return of the factors. It can be seen that the Trend factor Trend has been ranked No. 1 in 9 out of the total 12 years, outperforming all other momentum inversion factors. Meanwhile, the short-term inversion factor SREV, the medium-term momentum factor MOM, and the long-term inversion factor LREV each have negative returns in 3, 4, and 4 years, compared to which the Trend factor only has a negative value in 2019, and the loss value is small. Therefore, the relatively higher standard deviation of the trend factor than the other factors does not indicate that the factor is at risk of suffering losses more than the other factors.

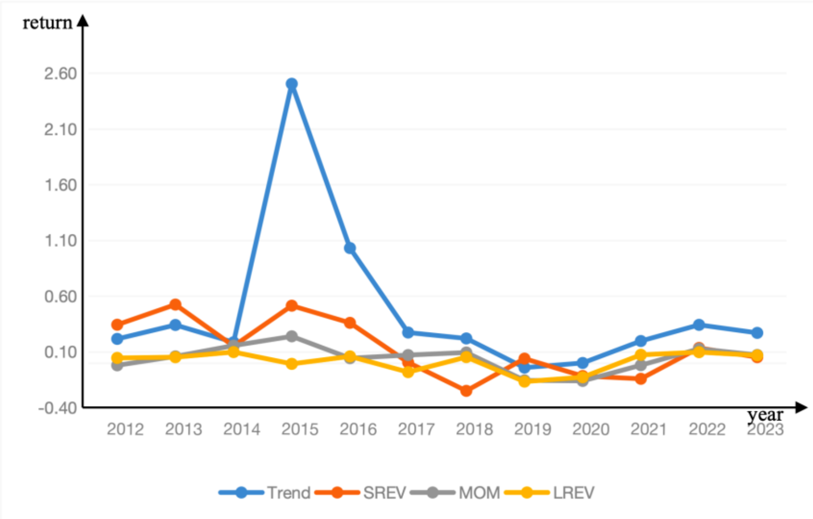

Figure 2 Ranking of annual returns by factor

It can be seen that the relatively large standard deviation of the Trend Factor is derived from extreme positive gains rather than losses, and that the Trend Factor is far more likely to achieve positive returns than other quantitative factors, presumably because it is able to take advantage of market opportunities over different time horizons by using moving averages to integrate short-, intermediate-, and long-term price information at the same time; and because it is formally more flexible because its conditions of use assume only that future stock prices will continue the trend exhibited in the past, without presupposing that this trend must be either momentum or reversal. Also, unlike traditional price factors that have a pre-determined direction of momentum or reversal, trend factors are formally more flexible in that their conditions of use assume that in the future the stock price will continue the trend it has shown in the past, without presupposing that the trend has to be either momentum or reversal.

2.4 Rank-IC sequence analysis

Information Coefficient (IC) is also a common way to test the validity of a factor, which is essentially a cross-sectional correlation coefficient between the corresponding factor value of a stock in the current period and its return in the next period. There are two common types of Information Coefficients, one is Normal-lC and the other is Rank-IC, the difference between the two is that the former calculates the Pearson correlation coefficient while the latter uses the Spearman rank correlation coefficient.

However, the Pearson correlation coefficients used in Normal-IC have strict requirements for the factor data and stock return data, firstly, both sets of data must satisfy the normal distribution and must be obtained in pairs from the normal data; and secondly, the data must be equally spaced. Obviously, it is difficult to find factor and return data in the real world that fully meet these conditions. Therefore, this paper chooses to use the Spearman rank correlation coefficient, which has more relaxed conditions, to construct the Rank-IC series, and calculates the rank correlation coefficient between the ranking of each stock's factor value in the current period and the ranking of the stock's return in the future period in each time cross-section, as follows:

$$Rank-IC = corr\left(\left\{order_t^{f_i}\right\},\left\{order_{t+1}^{r_i}\right\}\right) \tag{6}$$

Where, $order_t^{f_i}$ is the rank sequence of trend factor for each stock for the period t and $order_{t+1}^{r_i}$ is the rank sequence of return for each stock for the period $t+1$. The rank correlation coefficient of each period is calculated, then the Rank-IC information coefficient sequence of the trend factor is obtained. According to the experience of existing studies, when the absolute value of Rank-IC information coefficient is greater than 3%, the correlation between the factor value ranking and the stock return ranking is considered significant, which indicates that the factors have strong validity.

The Rank-IC information coefficient series for the trend factor over the sample period is shown in Figure 3, where the two straight lines have values of 3% and -3%, respectively. Table 3 further enumerates some important statistical features of the Rank-IC series. As can be seen from the table, the mean value of the Rank-IC information coefficient series is 7.5%, and the proportion of the absolute value of the Rank-IC information coefficient is greater than 3% is 0.864, which proves that the trend factor value has a high correlation with the stock's next return, and that the factor has a strong predictive ability for the return. Specifically, the proportion of positive and significant Rank-IC information coefficients is 0.621, and the proportion of negative and significant coefficients is 0.243, and the proportion of positive and significant coefficients is much higher than the proportion of negative and significant coefficients, because the value of the trend factor $E_t\left(r_{j,t+1}\right)$ is the prediction of the next period's return using the existing information of the current period, and the positive and significant Rank-IC indicates that the prediction value is in the same direction of the stock's actual return value, which proves that the predictive capacity of the trend factor is positive to the stock's return. This proves that the predictive ability of the trend factor on stock returns is positive, i.e., the larger the value of the trend factor in the current period, the higher the stock return in the next period. From the perspective of information coefficient series analysis, the trend factor also has good effectiveness in stock selection.

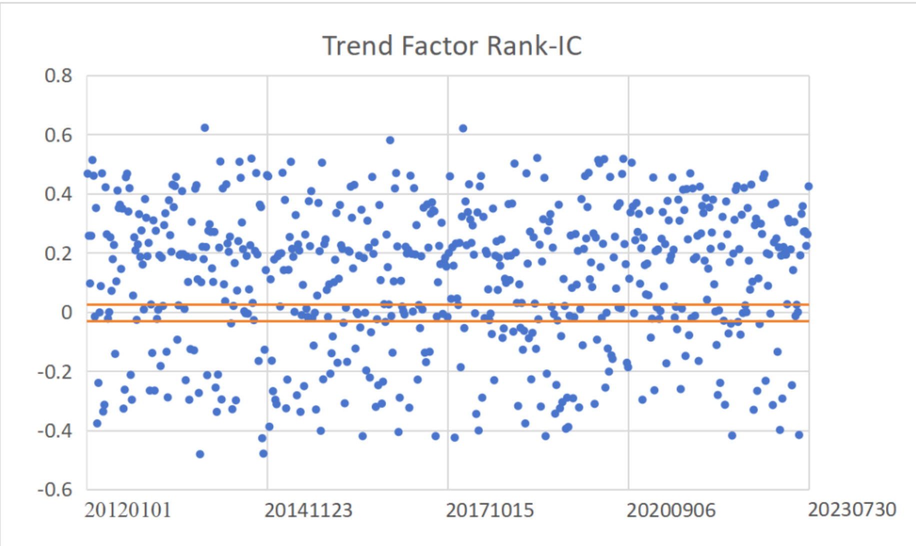

Figure 3 Sample period rank-IC sequence values

Table 3 Statistical results of Rank-IC series of trend factors.

indicator	value
Rank-IC sequence maximum	0.622
Rank-IC sequence minimum	-0.481
Rank-IC series mean	0.075
|Rank-IC|>3% ratio	0.864
Rank-IC positive significant ratio	0.621
Rank-IC negative significant ratio	0.243
Rank-IC Difference between positive and negative significant proportions	0.378

2.5 Trend factor returns under information uncertainty

Unlike technical analysis, which focuses on price movements in the market, fundamental traders focus on the long-term value of a stock, and when stock information is highly uncertain, the amount of valid information contained in this information that reflects the value of the stock decreases, and fundamental analysis is likely to fail, which will make investors tend to rely more on technical signals. Therefore, as a technical analysis factor, it is extremely important that the Trend Factor is able to show good stock selection effectiveness even under the state of information uncertainty.

Metrics such as market size, idiosyncratic volatility, stock turnover rate, and analyst coverage have been used in previous studies to represent information uncertainty. Given data availability, this paper chooses to use weekly stock turnover rate and firm age as proxies for information uncertainty and uses bivariate sorting to examine the performance of the trend factor under different levels of information uncertainty. Take the bivariate sorting of stock weekly turnover rate and trend factor as an example, first of all, according to the weekly turnover rate of each stock last week, the stocks in the market will be divided into 3 groups; and then in each group will be divided into 5 groups according to the trend factor, at this time, this paper will get 3*5 groups, and the stocks in each group will be combined with equal weights to get the returns of 3*5 portfolios. Thus, in each weekly turnover group there are 5 portfolios sorted by trend factor and in each trend factor group there are 3 portfolios sorted by weekly turnover. Finally; the high and low portfolios of the trend factors are constructed under each weekly turnover rate grouping to test whether there is any difference in the performance of the trend factors under different weekly turnover rates.

From Tables 4, it can be found that the trend factor earns stable positive returns under different information uncertainties and performs 0.08% better in the high turnover group than in the low turnover group, which proves that the trend factor becomes more predictive of stock returns when information uncertainty is higher.

Table 4 Bivariate ranking of turnover and trend factors.

			Trend			
Turnover	low	2	3	4	high	high-low
low	-0.02	0.23*	0.37**	0.38***	0.44**	0.46***
	(-0.12)	(1.72)	(2.45)	(4.33)	(2.52)	(3.36)
2	-0.11	0.19	0.35**	0.33*	0.39**	0.50***
	(-0.61)	(1.08)	(1.99)	(1.84)	(2.15)	(4.65)
high	-0.27**	-0.11	-0.01	0.08	0.27	0.54**
	(-1.99)	(-0.72)	(-0.56)	(0.46)	(1.47)	(2.49)
average over Turnover	-0.13	0.10	0.24***	0.26	0.37**	0.50**
	(-0.80)	(0.70)	(3.19)	(1.57)	(2.06)	(2.16)

Table 5 uses firm listing year as a proxy variable for information uncertainty, which is generally considered to be stronger the shorter the firm's listing time. It is empirically found that the trend factor yields significant positive returns at different levels of information uncertainty and is 0.04% higher in the short listing time group than in the long listing time group, which is consistent with the results obtained by using the weekly turnover rate as a proxy variable for information uncertainty.

Table 5 Bivariate ranking of firm age and trend factors.

			Trend			
Listing Age	low	2	3	4	high	high-low
old	0.06	0.25***	0.11	0.36**	0.48***	0.42**
	(0.40)	(3.73)	(1.01)	(2.38)	(3.18)	(2.58)
2	-0.12	0.27**	0.15*	0.21	0.16*	0.28**
	(-0.76)	(2.20)	(1.95)	(1.64)	(1.73)	(2.44)
young	-0.14*	0.03	0.24*	0.20***	0.32**	0.46***
	(-1.91)	(0.05)	(1.65)	(2.63)	(2.45)	(3.76)
average over Firm Age	-0.07	0.18	0.16	0.25**	0.32**	0.39***
	(-0.42)	(1.57)	(1.26)	(1.99)	(2.44)	(4.70)

This paper argues that the above results can be interpreted as a consequence of the interplay between the two types of investors in the HS model, the "news watchers" and the "momentum traders": the difficulty of predicting the fundamentals leads to a greater reliance on the technical aspects, and the proportion of "momentum traders" increases, while the rapid propagation of price signals among "momentum traders" leads to a further push up of the original price trend. The proportion of "momentum traders" in the market increases, and the rapid spread of price signals among "momentum traders" leads to a further push up of the original price trend, which makes investment strategies constructed on trend factors more profitable. As such, technical analysis essentially utilises information that is not the same as fundamental information, and the two are complementary. When fundamental information is interfered with, the technical information provided by the Trend Factor is better able to counteract information uncertainty in stock forecasting, and thus provides another way of thinking about how to maintain stable returns. Therefore, the study of trend factors is significant at this level.

2.6 Trend factor alpha returns

While this paper has demonstrated that significant returns can be obtained by portfolio analysis of the trend factor, it does not indicate whether the returns of the trend factor are derived from a combination of other pre-existing factors. The returns of the trend factor may be derived from some risky returns, so it is necessary to test whether the trend factor returns remain after risk adjustment. A common risk-adjusted adjustment method is to use the pricing factors in the classical asset pricing model to perform the Spanning Test on the target factor, and the Spanning Test chosen in this paper is to perform the Fama-French three-factor and Fama-French five-factor adjustment. If the model can fully explain the return of the trend factor, then the value of the intercept term α should be 0. On the contrary, if the value of the intercept term α is not 0, it means that the pricing factor in the model cannot explain the return of the trend factor. The model for performing the Spanning Test is shown in equations (7) and (8):

$$\mathrm{Trend}_t = \alpha + \beta \mathrm{MKT}_t + sSMB_t + hHML_t + \varepsilon_{i,t} \tag{7}$$

$$\mathrm{Trend}_t = \alpha + \beta \mathrm{MKT}_t + sSMB_t + hHML_t + rRMW_t + cCMA_t + \varepsilon_{i,t} \tag{8}$$

Table 6 presents the returns of α for the portfolios ranked from the highest to the lowest trend factor and the long-short portfolios adjusted by the Fama-French three-factor and Fama-French five-factor models. According to the table, the adjusted returns of $\mathrm{FF3}\alpha$ and $\mathrm{FF5}\alpha$ maintain a decreasing trend from the highest to the lowest trend factor group, which proves that the risk-adjusted portfolios still have good monotonicity among returns. The data results show that the returns of the long-short portfolio of the trend factor are still significant after the adjustment of the two models, which proves that the pricing factors in the Fama-French three-factor and Fama-French five-factor models do not explain the returns of this factor, and that the returns of the trend factor do not come from other risk factors.

2.7 Robustness tests

2.7.1 Changing the SMA indicator

In order to test the sensitivity of the trend factor returns to the selected moving average technical indicator, this paper examines the return series of the trend factor portfolios by varying the parameters of the SMA indicator, using $Lag = [3 \quad 7 \quad 10 \quad 20 \quad 50 \quad 100 \quad 200 \quad 250]$ and $Lag = [5 \quad 10 \quad 20 \quad 60 \quad 120 \quad 235]$ instead of the original moving average indicator, respectively.

According to Table 7, when the parameter of SMA is $Lag = [3 \quad 7 \quad 10 \quad 20 \quad 50 \quad 100 \quad 200 \quad 250]$, the returns of long-short portfolio, the returns of Fama-French three-factor-adjusted α, and the returns of Fama-French five-factor-adjusted α are 0.63%, 0.63%, and 0.61%, respectively, and the corresponding statistic of t is 4.76, 3.69, and 4.39, respectively, which are all significant at 1% level; the returns of ten portfolios constructed based on the magnitude of the trend factor still show a decreasing trend, which proves that the trend factor is still predictive under this set of SMA parameters. The ten portfolios constructed according to the size of the trend factor still show a decreasing trend, which proves that the trend factor is still predictive under the parameters of the mean index. When the parameter of SMA indicator is $Lag = \begin{bmatrix} 5 & 10 & 20 & 60 & 120 & 235 \end{bmatrix}$, the returns of long-short portfolio, the returns of Fama-French three-factor-adjusted α and the returns of Fama-French five-factor-adjusted α are 0.70%, 0.72% and 0.74%, respectively, and the corresponding statistics of t are 4.35, 4.77 and 3.73, which are all significant at 1% confidence level; the differences between different groups of trend factors are obvious. The difference is obvious, and the trend factor is effective under the group of mean indicators. It can be seen that the trend factor is not sensitive to the selection of mean technical indicators, and the return of the trend factor after replacing the mean indicators is still solid.

Table 6 Trend factor returns adjusted for the Fama-French three-factor model and the Fama-French five-factor model.

	mean (%)	FF3-alpha (%)	FF5-alpha (%)
Trend1	0.40***	0.39***	0.35***
	(3.06)	(3.85)	(2.75)
Trend2	0.39***	0.27***	0.31***
	(4.51)	(4.86)	(3.91)
Trend3	0.34**	0.33***	0.22*
	(2.43)	(3.17)	(1.85)
Trend4	0.38***	0.30***	0.32***
	(3.65)	(3.19)	(3.11)
Trend5	0.30**	0.26**	0.26**
	(2.19)	(2.34)	(2.31)
Trend6	0.28**	0.32***	0.18*
	(1.99)	(2.87)	(1.89)
Trend7	0.08	0.04	-0.06
	(0.51)	(0.43)	(-0.52)
Trend8	-0.12	-0.04	0.02
	(-1.01)	(-1.28)	(0.17)
Trend9	-0.15	-0.17**	-0.08
	(-0.85)	(-1.97)	(-0.83)
Trend10	-0.24*	-0.28*	-0.31**
	(-1.76)	(-1.72)	(-2.49)
high-low	0.64***	0.67***	0.66***
	(5.93)	(4.81)	(4.92)

2.7.2 Changing the scrolling period

In order to test the sensitivity of the trend factor returns to the rolling period, this paper examines the return series of the trend factor portfolios by varying the rolling period parameter, using N=26 and N=78 instead of the original 52-week rolling, respectively.

Table 8 reports the results of the sub-interval regressions for years N=26 and N=78. When a rolling period of 26 weeks is selected, the returns of the long-short portfolio, the Fama-French three-factor-adjusted α returns, and the Fama-French five-factor model-adjusted α returns are 0.71%, 0.66%, and 0.69%, respectively, which are significant at the 1% confidence level, with good monotonicity among the groupings of the trend factors; there is a roughly decreasing trend from the highest to the lowest group of the trend factors. When the selected rolling period is 78 weeks, the returns of the long-short portfolio, the Fama-French three-factor-adjusted α return and the Fama-French five-factor-adjusted α return are 0.55%, 0.50% and 0.56%, respectively, which are significant at the 1% confidence level, and there is a good monotonicity among the groups of trend factors. The trend factor returns and significance for the 78-week rolling are slightly lower than the 26-week rolling cycle, probably because the 78-week rolling cycle contains more noise, but the trend factor returns are significant within a reasonable range of rolling cycle choices, which proves that the trend factor returns are still robust after replacing the rolling cycle.

Table 7 Robustness tests for changing the parameters of the mean indicator lag.

	mean (%)	FF3-alpha (%)	FF5-alpha (%)
$Lag = [3 \quad 7 \quad 10 \quad 20 \quad 50 \quad 100 \quad 200 \quad 250]$			
Trend1	0.38**	0.36**	0.33***
	(2.48)	(2.06)	(3.13)
Trend2	0.40***	0.29**	0.35**
	(4.18)	(2.18)	(2.40)
Trend3	0.35***	0.34***	0.29***
	(3.48)	(5.31)	(3.98)
Trend4	0.40***	0.35***	0.32***
	(2.87)	(3.76)	(3.56)
Trend5	0.26*	0.24**	0.19
	(1.90)	(2.15)	(1.54)
Trend6	0.32**	0.28	0.22**
	(2.25)	(1.64)	(2.05)
Trend7	0.10	0.12	-0.01
	(0.86)	(1.04)	(-0.10)
Trend8	-0.13	-0.08	-0.11
	(-0.92)	(-0.96)	(-1.04)
Trend9	-0.18	-0.14	-0.10
	(-1.25)	(-1.19)	(-1.20)
Trend10	-0.25*	-0.27**	-0.28**
	(-1.67)	(-2.47)	(-2.56)
high-low	0.63***	0.63***	0.61***
	(4.76)	(3.69)	(4.39)
$Lag = [5 \quad 10 \quad 20 \quad 60 \quad 120 \quad 235]$			
Trend1	0.43***	0.37**	0.39**
	(2.79)	(2.51)	(2.13)
Trend2	0.37***	0.32	0.29*
	(3.60)	(1.50)	(1.72)
Trend3	0.30**	0.37***	0.32***
	(2.15)	(2.91)	(2.79)
Trend4	0.38***	0.45***	0.31**
	(2.72)	(3.61)	(2.24)
Trend5	0.31**	0.23**	0.25**
	(2.21)	(2.28)	(2.31)
Trend6	0.30**	0.28***	0.32***
	(2.18)	(3.08)	(3.74)
Trend7	0.15	0.06	0.02
	(1.06)	(0.51)	(0.21)
Trend8	-0.14	-0.18*	-0.18
	(-1.00)	(-1.80)	(-1.54)
Trend9	-0.16	-0.15	-0.12
	(-1.11)	(-1.42)	(-1.20)
Trend10	-0.27**	-0.35**	-0.35***
	(-2.32)	(-2.38)	(-2.74)
high-low	0.70***	0.72***	0.74***
	(4.35)	(4.77)	(3.73)

Table 8 Robustness test for changing rolling period N

N=26			
	Mean (%)	FF3-alpha (%)	FF5-alpha (%)
Trend1	0.46***	0.36***	0.39***
	(5.01)	(3.88)	(2.63)
Trend2	0.55***	0.41***	0.45**
	(3.00)	(2.65)	(2.50)
Trend3	0.42*	0.44**	0.34**
	(1.85)	(2.36)	(2.38)
Trend4	0.48***	0.26*	0.43***
	(2.74)	(1.82)	(3.25)
Trend5	0.38**	0.33*	0.23**
	(2.17)	(1.70)	(1.98)
Trend6	0.35**	0.35*	0.48***
	(2.21)	(1.75)	(2.83)
Trend7	-0.12	0.06	-0.06
	(-0.69)	(0.36)	(-0.80)
Trend8	-0.14	-0.21*	0.00
	(-0.80)	(-1.91)	(0.00)
Trend9	-0.17	-0.24**	-0.18
	(-1.34)	(-2.07)	(-1.31)
Trend10	-0.25*	-0.30**	-0.30*
	(-1.68)	(-2.36)	(-1.83)
high-low	0.71***	0.66***	0.69***
	(4.63)	(5.15)	(4.34)
N=78			
	Mean (%)	FF3-alpha (%)	FF5-alpha (%)
Trend1	0.27*	0.26***	0.34***
	(1.75)	(2.65)	(2.66)
Trend2	0.22*	0.12*	0.16**
	(1.65)	(1.74)	(2.06)
Trend3	0.26***	0.33**	0.09
	(2.99)	(2.51)	(1.40)
Trend4	0.28**	0.36*	0.20**
	(2.02)	(1.90)	(2.11)
Trend5	0.22	0.19	0.30**
	(1.63)	(0.90)	(2.03)
Trend6	0.21	0.30	-0.05
	(1.44)	(1.47)	(-0.49)
Trend7	0.32*	0.02	-0.06
	(1.84)	(-0.32)	(-0.65)
Trend8	-0.10	0.16	0.04
	(-0.69)	(1.05)	(0.48)
Trend9	-0.13	-0.09	0.03
	(-0.98)	(-0.61)	(0.55)
Trend10	-0.28*	-0.24	-0.22**
	(-1.90)	(-1.29)	(-2.24)
high-low	0.55***	0.50***	0.56***
	(2.76)	(3.26)	(3.88)

3. Empirical Test of Improved Fama-French Five-Factor Model Based on Trend Factors

3.1 Modelling

3.1.1 TRE factor construction

Based on the verification of the effectiveness of the trend factor in the previous paper, this paper will further test whether the combination of the trend factor with the pricing factors in the classical asset pricing model can better reveal the law of Chinese stocks in pricing. Meanwhile, the traditional Fama-French five-factor model has been widely used in the Chinese market, but in response to its still unexplained excess returns, some scholars have improved the model, such as adding a liquidity factor[21], an investor sentiment index factor and a consumption risk premium factor[22], and a total factor productivity factor[23].

In order to achieve the unity of portfolio construction with other pricing factors, this paper modifies the aforementioned trend factor, adopts the factor construction method in the five-factor model, constructs the TRE factor according to the method of constructing the value factor, and incorporates the trend factor into the Fama-French five-factor model. The TRE factor is constructed as follows: firstly, companies are divided into large market capitalisation group (B) and small market capitalisation group (S) according to their market capitalisation; then they are divided into high expectation (T), medium expectation (R) and low expectation (E) according to the expectation of the next period's return using the past average indicator in 30% and 70% quartiles, and then the two groupings are ranked and combined to obtain six portfolios, namely, BT, BR, BE, ST, SR, and SE. The returns of the six corresponding portfolios are denoted as r_{BT}, r_{BR}, r_{BE}, S_{ST}, r_{SR}, r_{SE} then the TRE factor is calculated as equation (9):

$$\mathrm{TRE}=\frac{r_{\mathrm{BT}}+r_{\mathrm{ST}}}{3}-\frac{r_{\mathrm{BE}}+r_{\mathrm{SE}}}{3} \tag{9}$$

Excluding the trending factors, the construction methodologies for the remaining factors have been previously delineated. The factor data, sourced from the CSMAR (China Stock Market & Accounting Research) database, have been categorized employing a 2-by-3 grouping schema, thereby facilitating a nuanced analysis of distinct market segments.

3.1.2 Redundant factor test

Before explaining stock returns using a model that incorporates trend factors, the performance of the factors is first examined together to test whether redundant factors need to be eliminated. Three methods are used here to test the average returns of the factors and the correlation coefficients between the factors, and then regress the returns of each factor against the returns of the other factors.

Table 9 demonstrates the descriptive statistics of the factors. According to the table, for the classical FF, the weekly average return of the size factor SMB reaches 0.189% and is significant at the 5% confidence level, which proves that the small market capitalisation effect is obvious in the Chinese stock market; whereas the weekly average return of the profitability factor CMA is only -0.005%, which is very small and insignificant, and initially, it is believed that the profitability factor CMA may be a redundant factor. Meanwhile, the weekly average return of Trend Factor TRE is 0.438%, and it is significant at 1% level, which outperforms the classic FF five factors.

Table 9 Descriptive statistics.

	mean (%)	std (%)	min (%)	max (%)
MKT	0.138	2.786	-13.377	10.169
	(1.23)			
SMB	0.189**	2.142	-12.722	10.914
	(2.17)			
HML	0.027	1.776	-7.204	8.743
	(0.39)			
RMW	-0.005	1.389	-5.636	9.384
	(-0.09)			
CMA	0.017	1.281	-5.813	4.063
	(0.32)			
TRE	0.438***	2.890	-10.040	19.420
	(3.73)			

According to the factor correlation coefficients shown in Table 10, the absolute value of the correlation coefficient between the newly added trend factor TRE and the other five factors is less than 0.3 and less significant, which is consistent with the previous conclusions, proving that the price signals captured by the trend factor have a lower correlation with the fundamental value signals; the correlation coefficients of the profitability factor RMW and the other four factors, except for the market factor MKT, are all significant, and with the size, Value and Investment factors, and the absolute value of the correlation coefficients of all three factors exceeds 0.4, proving that the profitability factor is likely to have multicollinearity with other factors.

Table 10 Factor correlation analysis.

	MKT	SMB	HML	RMW	CMA	TRE
MKT	1.000					
SMB	0.160*	1.000				
HML	-0.229**	-0.647***	1.000			
RMW	-0.217	-0.609***	0.448**	1.000		
CMA	0.023	0.337*	0.146	-0.584***	1.000	
TRE	-0.135	0.270*	-0.057	0.189**	-0.104	1.000

Finally this paper uses the redundant factor test proposed by Fama and French (2015)[24] to regress the returns of the target factor with the other factors against the returns of the target factor, the intercept term is significantly non-zero then the factor is not redundant, the intercept term is not significantly non-zero then the factor is able to be explained by the other factors then it is a redundant factor. The results of explaining the sixth factor with the remaining five factors are shown in Table 11. From the table, it can be seen that the intercept term after regression of RMW with other factors is 0.021% and the value of t is 0.39, which proves that the profitability factor RMW is explained by other factors is very small and insignificant, and the return of RMW factor can be explained by the other five factors.

Table 11 Results of Fama-French redundant factor test.

	MKT	SMB	HML	RMW	CMA	TRE
_cons	0.230***	0.316***	0.087	0.021	-0.081	0.384***
	(3.21)	(4.49)	(1.47)	(0.39)	(-1.13)	(3.83)

Comprehensive factor returns, correlation analysis and Fama-French redundancy test triple analysis, this paper believes that RMW is a redundant factor in the model, which is removed, and the trend factor TRE is added to the model. Therefore, the improved five-factor model finally constructed is:

$$R_{i,t} - R_{f,t} = \alpha + \beta MKT_t + sSMB_t + hHML_t + cCMA_t + dTRE_t \tag{10}$$

3.2 Subgroup regression test

In order to test whether the improved Fama-French five-factor model has pricing power in the Chinese stock market, this paper constructs 5*5 portfolios in terms of size-to-book-to-market ratio, size-to-investment, and size-to-trend, respectively, and gives an analysis of the model's overall explanatory power and the performance of each factor.

3.2.1 Size-value grouping regression results

Table 12 reports the coefficients of each factor and the model goodness of fit for regressions on 5*5 subgroups constructed with size and book-to-market ratios.

Overall, out of the 25 intercept terms α , 7 are significantly non-zero and the remaining 18 intercept terms are non-significant, proving that the original hypothesis of zero cannot be rejected and that the improved five-factor model using the trend factor to replace the profitability factor is able to explain most of the stock returns. Meanwhile, the Adj-R^2 of the model are around 0.9, which indicates that the model has a good fit.

Table 12 Regression results for ME-BM subgroups.

ME-BM										
	BM									
ME	1	2	3	4	5	1	2	3	4	5
	α					t(α)				
1	0.096*	0.083**	0.094**	0.049	0.045	1.759	2.243	2.306	1.093	0.878
2	-0.092*	-0.065	-0.002	0.059	-0.028	-1.941	-1.433	-0.060	1.511	-0.743
3	-0.071	-0.035	-0.021	0.064	0.004	-1.267	-1.106	-0.370	1.506	0.092
4	-0.095	-0.101**	-0.079	0.072	0.057	-1.627	-2.308	-1.466	1.620	1.300
5	0.179***	0.090	-0.083*	-0.024	0.028	3.853	1.380	-1.805	-0.391	1.222
	β					t(β)				
1	0.972***	1.045***	0.913***	1.085***	0.982***	20.592	30.228	24.990	24.526	21.172
2	0.893***	0.996***	0.923***	1.115***	0.962***	30.177	45.947	37.853	65.195	55.011
3	0.873***	0.997***	0.884***	1.209***	1.053***	45.587	29.200	53.701	39.256	25.435
4	0.797***	0.972***	0.978***	1.203***	1.059***	41.820	26.764	36.067	47.437	47.607
5	0.820***	1.091***	1.062***	1.245***	0.877***	29.835	41.703	43.881	51.151	31.059
	s					t(s)				
1	1.055***	1.098***	0.996***	1.079***	0.920***	18.682	7.840	10.436	23.117	23.783
2	0.947***	1.027***	0.868***	1.011***	0.651***	26.188	18.090	24.629	21.707	27.894
3	0.698***	0.761***	0.683***	0.613***	0.451***	18.345	22.849	15.896	14.930	16.107
4	0.408***	0.474***	0.361***	0.406***	0.254***	11.290	11.135	8.498	9.086	8.544
5	-0.587***	-0.256***	-0.335***	-0.162***	-0.132***	-11.604	-5.504	-8.823	-3.460	-5.433
	h					t(h)				
1	-0.141	-0.129**	-0.069	0.082	0.176***	-1.565	-2.234	-1.139	1.570	3.175
2	-0.225***	-0.108	-0.049	0.083*	0.194***	-3.615	-0.777	-0.651	1.674	4.776
3	-0.354***	-0.230***	-0.149**	0.001	0.211***	-4.525	-4.260	-2.258	0.015	4.104
4	-0.451***	-0.235***	-0.112	0.067	0.266***	-6.419	-3.507	-1.291	0.928	4.483
5	-0.840***	-0.272***	-0.059	0.216*	0.303***	-10.707	-3.949	-0.806	1.874	9.053
	c					t(c)				
1	0.026	0.047	0.100	0.066	0.095	0.378	0.493	1.450	0.897	1.124
2	0.061	0.017	0.138*	0.120	0.218***	0.690	0.194	1.948	1.607	3.220
3	0.001	0.136**	0.158	0.182**	0.046	0.009	2.215	1.421	2.296	0.675
4	0.002	0.181*	0.166*	0.238***	0.217***	0.032	1.890	1.744	2.977	3.093
5	0.061	0.141	0.174*	0.140	0.064	0.493	1.334	1.855	1.454	1.153
	d					t(d)				
1	0.097***	0.042**	0.063***	0.019	0.005	3.944	2.418	4.389	1.102	0.306
2	0.096	0.070***	0.034**	-0.011	-0.029*	1.642	2.978	2.322	-0.591	-1.950
3	0.127***	0.021	0.061*	0.065***	0.004	4.635	1.554	1.921	2.998	0.170
4	0.069**	0.028	0.027	0.048**	-0.063***	2.563	1.189	1.031	2.061	-3.547
5	0.110***	0.218***	0.049**	-0.030***	-0.127***	5.314	7.284	1.995	-2.523	-8.920
	Adj-R2									
1	0.935	0.943	0.936	0.938	0.908					
2	0.938	0.952	0.944	0.930	0.915					
3	0.962	0.879	0.832	0.973	0.998					
4	0.931	0.933	0.923	0.907	0.961					
5	0.965	0.988	0.962	0.902	0.979					

In terms of the performance of the factors, the coefficients of the market factor β are all significant at the 1% level among the 25 subgroups, and there is no obvious trend of change in the subgroups of size and value from small to large, which proves that all the stocks in the market have a portion of excess returns from the risk compensation of the market's systematic risk, and there is no doubt that the market factor has a strong explanatory power of the stock returns. The coefficients of the scale factor s are also all significant at 1% level, indicating that the scale effect is significant, and from the trend of the scale factor coefficients, the explanatory power of the scale factor is gradually weakened with the expansion of the scale factor, which indicates that when the investment object is a small-capitalisation stock, the investor is more concerned about the volatility arising from the difficulty of obtaining stock information and facing the manipulation of the stock price and expects to get more compensation when investing in small-capitalisation stocks; Meanwhile, as the book-to-market ratio increases, the coefficient of the size factor shows a decreasing trend, which indicates that for stocks that are severely undervalued, investors may pay more attention to the deviation from the price and value of the stock rather than the risk compensation requirements arising from the low market capitalisation, and that the explanatory power of the size factor becomes weaker in high-value stocks. Book-to-market ratio factor coefficients h have 16 significant non-zero, indicating that the value effect is significant; at the same time, from the trend of change, with the increase of book-to-market ratio value factor coefficients show an increasing trend, value factor coefficients turn from negative to positive, indicating that investors facing the growth company rely more on the market's valuation of the stock to judge the company's investment prospects, while investors in the value company make more use of the undervaluation of stock prices to profit. The coefficients of the investment factor c have 9 coefficients significantly not 0, which proves that the explanatory power of the investment factor is not strong under this grouping; the coefficients of the investment factor increase with the increase of the ratio of book-to-market and the significance is stronger in the latter two groups, which indicates that the investment factor has a stronger explanatory rate of the returns of the value-oriented companies.

Finally, looking at the performance of the trend factor, 17 of the trend factor coefficients *d are* significantly non-zero, second only to the market and size factors, proving that price trends generated in the market in the past can explain the excess returns of stocks and that the trend factor has a significant impact on stock returns. As the book-to-market ratio increases, the coefficient of the trend factor turns from positive to negative, proving that the trend factor may be more suitable for analysing growth stocks, perhaps because growth stocks receive more attention from investors and are more likely to generate price trends.

3.2.2 Regression results for size-investment subgroups

Table 13 reports the regression results for the size-investment 5*5 subgroup. In the size-investment subgroup, there are 19 intercept terms α accepting the null hypothesis, the model is able to explain most of the excess returns and the Adj-R^2 is also around 0.9, the model has strong pricing power in the size-investment portfolio.

From the performance of each factor, the coefficient of market factor β and the coefficient of size factor s are still all significant at 1% level, which proves that these two have strong explanatory ability for stock returns. The coefficient of book-to-market factor h has 17 non-zero, the book-to-market factor has strong explanatory ability, and from the trend of change, it seems that the coefficient of book-to-market factor shows an increasing trend with the increase of investment, which may be that the sufficient capital of the company gives the signal of the company's strong substantive profitability, which makes the value-oriented investors prefer this kind of stock. The coefficient of investment factor c has 16 significant non-zero, which proves that the explanation of investment factor is stronger under the grouping of scale-investment, and the direction of the influence of investment factor with the increase of investment turns from positive in the first three groups to negative in the last two groups, which is speculated that perhaps the gain of investment factor for the company with relatively conservative investment style comes from the compensation for the insufficient diversification of investment risk; while in the company with the most aggressive investment style the high The retained portion of the investment comes from fewer stock payouts.

The coefficient of the trend factor d has 13 significant non-zeroes, which is a mediocre performance compared to the other two groupings, but still half of the portfolio returns can be explained by the trend factor. The coefficient of the trend factor has 4 negative values in the 5 highest invested portfolios, proving that the trend factor is more suited to low investment rather than high investment stocks, which may be due to the fact that high investment leads to long term returns while technical analysis focuses more on short term returns and different investment philosophies using the two types of investment strategies.

Table 13. Regression results for ME-INV subgroups.

ME-INV

	INV									
ME	1	2	3	4	5	1	2	3	4	5
	α					t(α)				
1	0.037	0.059*	0.103**	0.134***	0.022	1.195	1.738	2.272	2.716	0.439
2	-0.042	-0.001	-0.052*	0.018	-0.009	-1.224	-0.035	-1.838	0.568	-0.269
3	0.050	0.011	-0.033	0.013	-0.054	1.188	0.365	-0.864	0.354	-1.035
4	-0.106**	-0.039	-0.015	-0.088**	0.031	-2.292	-0.826	-0.366	-2.076	0.600
5	0.018	-0.061	0.069**	0.160***	0.021	0.337	-1.173	2.107	4.247	0.483
	β					t(β)				
1	0.967***	0.960***	1.083***	1.082***	1.032***	29.055	34.158	35.218	25.020	62.537
2	0.968***	0.980***	1.005***	0.971***	1.047***	39.523	20.287	36.124	29.226	32.188
3	0.967***	0.987***	0.984***	1.074***	1.072***	17.928	34.772	20.910	38.043	28.542
4	1.013***	0.961***	1.046***	1.030***	1.042***	35.841	16.471	23.019	49.287	55.825
5	1.084***	0.901***	0.938***	1.119***	1.183***	53.852	26.516	30.802	34.965	41.933
	s					t(s)				
1	1.142***	0.939***	0.969***	1.121***	0.937***	16.353	24.678	18.655	23.953	19.805
2	1.056***	0.854***	0.887***	1.193***	0.772***	10.237	21.515	26.327	20.259	21.592
3	0.608***	0.507***	0.671***	1.057***	0.484***	18.110	18.888	23.717	10.982	15.156
4	0.498***	0.617***	0.640***	0.887***	0.445***	13.661	12.598	9.400	15.193	3.464
5	-0.325***	-0.178***	-0.308***	-0.350***	-0.230***	-8.575	-5.464	-12.246	-11.763	-6.739
	h					t(h)				
1	0.010	0.021	-0.063	0.158	0.168	1.372	0.470	-1.240	0.823	1.508
2	0.078	-0.091	0.099	0.234***	0.223**	1.419	-0.072	0.214	3.901	2.212
3	0.119**	0.120**	0.228***	0.222**	0.350***	2.408	2.493	5.144	2.178	5.754
4	0.105	-0.109	0.150**	0.185***	-0.534***	1.593	-0.133	2.518	3.473	-6.556
5	0.223***	0.238***	0.211***	0.207***	0.227***	3.188	3.838	4.184	3.768	4.175
	c					t(c)				
1	0.130**	0.163*	0.162*	-0.140*	-0.249***	2.158	1.790	1.801	-1.958	-2.966
2	0.127*	0.119*	0.055	0.027	-0.307***	1.833	1.935	0.668	0.347	-4.301
3	0.136*	0.034	0.029	-0.095	-0.265**	1.681	0.426	0.368	-1.093	-2.494
4	0.144	0.121	-0.020	-0.144*	-0.278***	1.012	0.934	-0.238	-1.785	-2.617
5	0.358***	0.313***	0.036	-0.142*	-0.287***	3.379	3.197	0.562	-1.824	-3.386
	d					t(d)				
1	0.073**	0.093***	0.075*	0.075	-0.052	2.121	3.405	1.959	1.578	-1.122
2	0.036	0.036	0.069***	-0.027	-0.061	0.990	1.032	2.770	-0.947	-1.012
3	-0.127***	-0.051*	0.029	0.042	0.110**	-3.009	-1.712	0.804	1.171	2.571
4	0.161***	0.112***	0.072	0.025	-0.168***	3.916	2.770	1.438	0.572	-3.271
5	-0.076	0.014	-0.086***	-0.198***	0.109**	-1.420	0.280	-2.943	-5.641	2.568
	Adj-R2									
1	0.957	0.901	0.961	0.925	0.947					
2	0.858	0.906	0.963	0.834	0.955					
3	0.957	0.902	0.861	0.924	0.943					
4	0.922	0.895	0.955	0.915	0.917					
5	0.909	0.879	0.936	0.918	0.898					

3.2.3 Regression results for size-trend grouping

Table 14 reports the regression results for the size-trend 5*5 subgroup. Of the 25 intercept terms α , 7 are significantly non-zero, 18 intercept terms cannot reject the original hypothesis of zero, and Adj-R^2 is around 0.9, the model has strong explanatory power for portfolios grouped by size-trend ratio.

Looking at the performance of the factors, the market factor coefficient β and the size factor coefficient s remain significant with 25 and 23 significant non-zero coefficients, respectively; the coefficient of the size factor increases as the trend of the stock strengthens, perhaps because a low trend tends to imply that fewer investors are paying attention and the proportion of investors with inside information increases for these cold stocks, thus the value effect becomes smaller. The coefficient of the book-to-market ratio factor *h* has 11 significant items and the coefficient of the investment factor *c* has 12 significant items, both factors are average in performance and there is no significant trend, presumably due to the fact that the trend factor, which is a technical analysis factor, brings higher returns under this grouping, which leads to a weakening of the validity of book-to-market ratio factor and the investment factor, which are fundamental factors.

Table 14 Regression results for ME-TRE subgroups.

ME-TRE										
	TRE									
ME	1	2	3	4	5	1	2	3	4	5
	α					t(α)				
1	0.069**	0.099***	0.033	0.089*	0.041	2.169	3.212	1.019	1.913	0.765
2	-0.027	0.004	-0.018	-0.016	-0.056	-0.708	0.125	-0.501	-0.515	-1.155
3	0.075	-0.033	-0.013	0.040	-0.101*	1.605	-1.116	-0.342	0.986	-1.815
4	-0.009	-0.090*	-0.067	-0.033	-0.032	-0.185	-1.947	-1.339	-0.785	-0.777
5	0.048	0.039	-0.134**	0.027	0.117***	0.792	0.722	-1.993	0.488	4.242
	β					t(β)				
1	1.098***	1.034***	0.955***	0.955***	1.144***	39.394	46.508	32.185	19.086	38.138
2	1.070***	1.018***	0.881***	0.973***	1.201***	20.847	29.608	48.216	47.457	32.557
3	1.061***	1.089***	0.944***	1.006***	1.074***	27.196	33.383	32.574	28.161	18.575
4	1.105***	1.042***	0.968***	1.008***	1.081***	35.083	60.700	31.190	28.729	26.780
5	1.086***	1.090***	1.073***	0.980***	1.063***	49.773	34.102	35.915	34.958	54.724
	s					t(s)				
1	0.833***	0.917***	1.092***	1.028***	1.006***	18.984	8.311	29.464	8.890	19.166
2	0.683***	0.701***	1.025***	1.045***	1.810***	22.165	17.164	34.071	24.632	18.726
3	0.420***	0.577***	0.713***	0.690***	1.646***	7.445	22.669	23.739	18.008	19.370
4	0.258***	0.372***	0.440***	0.400***	0.550***	4.462	9.193	15.348	13.806	8.309
5	-0.027	-0.282***	-0.071	-0.218***	-0.071***	-0.461	-7.629	-1.381	-5.231	-7.018
	h					t(h)				
1	0.033	-0.036	-0.005	-0.162**	0.030	0.644	-0.863	-0.095	-2.356	0.307
2	0.033	0.083*	-0.090	-0.040	-0.064	0.484	1.710	-1.579	-0.943	-0.732
3	-0.200***	-0.227***	0.290***	-0.272***	-0.173***	-2.945	-4.944	5.971	-4.978	-3.632
4	0.013	-0.118	-0.204***	-0.220***	-0.345***	0.137	-1.576	-3.326	-4.332	-5.482
5	-0.116	0.062	0.362***	0.048	-0.054	-1.183	0.887	3.448	0.538	-0.822
	c					t(c)				
1	0.231	0.270	0.220**	0.196	-0.383***	1.239	1.363	2.227	0.978	-2.984
2	0.078	0.197**	-0.043	0.192*	-0.472**	0.567	2.341	-0.415	1.686	-1.970
3	0.041	-0.057	-0.149	0.206***	0.408***	1.043	-1.464	-0.916	3.385	3.656
4	0.028	0.021	-0.226	-0.217	-0.428**	1.416	0.956	-1.477	-1.240	-2.404
5	0.052	0.517***	0.223**	-0.541**	-0.883***	1.291	4.021	2.136	-2.090	-6.656
	d					t(d)				
1	0.024*	0.035*	0.060	-0.063**	0.067**	1.955	1.680	1.564	-2.365	1.969
2	0.012	0.014	0.020*	0.039*	0.045	1.544	0.568	1.659	1.688	1.151
3	0.134***	0.170***	0.177***	0.254***	0.249***	3.313	4.777	4.207	6.498	5.100
4	0.015	0.011	0.001	0.062***	0.060*	0.376	0.342	0.045	2.729	1.713
5	-0.107**	0.040	0.129***	-0.083**	-0.077***	-2.225	1.237	4.249	-2.030	-3.776
	Adj-R2									
1	0.931	0.962	0.923	0.926	0.891					
2	0.925	0.962	0.926	0.948	0.899					
3	0.919	0.961	0.924	0.930	0.896					
4	0.884	0.936	0.911	0.941	0.898					
5	0.871	0.916	0.841	0.901	0.907					

Trend factor coefficient *d* of the 25 subgroups in 17 groups is significantly not 0, indicating that the trend factor under this subgroup has a strong explanatory ability for stock returns; from the trend of change, the trend factor in different subgroups between the trend factor has a significant difference from the trend of the weakest to the strongest group shows an increasing trend, proving that investors based on the past trend of the expected return inferred investment decisions can be access to the excess return, trend factor has a strong ability to explain stock returns.

5. Conclusions

The core work of this paper is to find technical indicators different from those other than the traditional momentum or reversal factors, to give an explanation in line with market practice as to whether the financial anomaly of the trend effect can predict stock returns in China's market as well as its prediction mechanism, and to make a study of the pricing law of China's stock market based on the combination of the trend factor and the classical asset pricing model. With this purpose, this paper constructs the trend factor of A-share market with reference to Han et al. (2016)[1] and makes an empirical test on the performance of the trend factor and the Fama-French five-factor model combined with the trend factor in China's stock market.

The empirical results of this paper suggest that the trend factor has a strong predictive ability for stock returns. In the constructed ten-position portfolio of trend factor, from the highest to the lowest factor group returns show very obvious decreasing characteristics, and has obvious extreme value difference, from the degree of differentiation between the groups of trend factor has a very good stock selection effectiveness; in terms of the average factor returns, trend factor returns are much higher than short-term inversion factor, medium-term momentum factor and long-term inversion factor and other quantitative factors, and will be the four factor's Comparing the annual returns of the four factors, it is found that the trend factor is steadily higher than the other factors in most of the years, the trend factor is exposed to less risk of loss and has the characteristic of still obtaining high returns when the stock market fluctuates violently; the trend factor obtains significant positive returns under different levels of information uncertainty, and even performs better when the level of information uncertainty is even higher, which proves that the technical analysis can be used as a supplement to fundamental analysis; after the Fama-Trend analysis, the trend factor has a higher return than the other factors, and the trend factor is even better than the other factors. This proves that technical analysis can complement fundamental analysis; the alpha return of the trend factor is still very significant after Fama-French's three-factor and five-factor adjustments, and the significance of the return is still the same after replacing different SMAs and rolling window periods for the robustness test, which proves that the return of the trend factor does not come from the compensation of the risk of the pricing factors in the market, but rather, the source of the trend factor is the trend effect that really exists in the market.

At the same time, this paper goes further by incorporating the trend factor into the Fama-French five-factor model, combining the asset pricing model in behavioural finance and traditional finance, and testing that this improved asset pricing model has the explanatory ability for the stock pricing in China's market, which indicates that the improved Fama-French five-factor model proposed in this paper has a good pricing ability.

The research in this paper has certain significance for investors. For individual investors, they should improve their own cognitive level, for different ways of measurement, different periods of technical indicators for comprehensive consideration, enhance the ability to accurately judge the technical information, so that the technical aspects of the choice of trading time, to grasp the opportunity to start the bottom of the market; and when the phenomenon of investor overreaction, under-reaction and other phenomena leading to a serious deviation of stock prices from the value of the gradual accumulation of risk increases, investors should consider timely exit to prevent losses caused by market reversal. Investors should consider timely withdrawal to prevent losses caused by market reversal.

For institutional investors, in the development of trading strategies, you can make full use of their own information advantage and capital advantage, technical changes in the stock returns into the consideration of the development of trading strategies, combined with the price-volume relationship in order to build a more accurate and comprehensive trend factors, trend changes into the quantitative model, to provide new ideas and methods for trading.

This paper also has some shortcomings. For example, there is a single method of constructing the trend factor; only the Fama-French five-factor model is chosen for the selection of the asset pricing model, and it fails to explore the model performance of combining the trend factor with other models. Future research could, on the one hand, further target trend factors that take into account changes in historical returns, incorporate new trend factors into asset pricing models, and explore ways to enhance the pricing power of trend factors. On the other hand, it can try to use other asset pricing models, such as the Fama-French three-factor model, the four-factor model based on total factor productivity, the Q-model, etc., and combine the trend factor with different models in order to test whether better explanatory power can be obtained.

Acknowledgments

This paper is founded by project Research on the impact of Board strategic participation on governance performance from the perspective of green governance (ZR2023QG160) supported by Shandong Provincial Natural Science Foundation; Research on the reform of strategic management courses (Y2024012) supported by Shandong University (Weihai).

References

[1] Fama E F. The behaviour of stock-market prices. The Journal of Business, 1965, 38(1): 34-105.
[2] Barberis N, Shleifer A, Vishny R. A model of investor sentiment. Journal of Financial Economics, 1998, 49(3): 307-343.
[3] Daniel K, Hirshleifer D, Subrahmanyam A. Investor psychology and security market under- and overreactions. The Journal of Finance, 1998, 53(6): 1839-1885.
[4] Hong H, Stein J C. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance, 1999, 54(6): 2143-2184.
[5] Han Y, Zhou G, Zhu Y. A trend factor: any economic gains from using information over investment horizons? Journal of Financial Economics, 2016, 122(2): 352-375.
[6] Zhu Y, Zhou G. Technical analysis: an asset allocation perspective on the use of moving averages. Journal of Financial Economics, 2009, 92(3): 519-544.
[7] Han Y, Lesmond D. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. The Review of Financial Studies, 2011, 24(5): 1590-1629.
[8] Yuan Jun. Technical analysis and asset pricing. Beijing: University of International Business and Economics, 2018.
[9] Fama E F, French K R. The cross-section of expected stock returns. The Journal of Finance, 1992, 47(2): 427-465.
[10] Efficiency S M. Returns to Buying Winners and Selling Losers: Implications for. The Journal of Finance, 1993, 48(1): 65-91.
[11] Qi Yulu, Wang Zhiqiang. Analysis of enhanced price reversal strategy introducing surplus momentum and revenue momentum. Investment Research, 2015, 3: 92-106.
[12] Lu Rong, Chen Shi, Li Jinlong. Lottery Stocks and the Momentum Effect. Economics Dynamics, 2021, (07): 34-50.
[13] Deng Xuebin, Xianxin Hao, Shan Haochen. A study on momentum and reversal effects in China's A-share market - A re-test based on the improved HS model of turnover. Forecasting, 2021, 40(04): 53-59.
[14] He Jingtong, He Kun, Zhao Zimu, Zheng Weiyi. Short-run reversal and long-run reversal of the Chinese stock market: empirical facts, theoretical models and experimental simulations. Nankai Economic Research, 2021(01): 85-101+224.
[15] Jiang Danling, Peng Xun, Zhu Hongquan. A study of stock momentum spillovers of A-share affiliates - Based on the perspective of analysts' common coverage. Systems Engineering Theory and Practice, 2023.
[16] Qu Ronghua, Liu Yang. Overnight-intraday reversal effect in Chinese A-shares. Economic Journal, 2020, 7(04): 64-87.
[17] Geczy C C, Samonov M. Two centuries of price-return momentum. Financial Analysts Journal, 2016, 72(5): 32-56.
[18] Lim B Y, Wang J G, Yao Y. Time-series momentum in nearly 100 years of stock returns. Journal of Banking & Finance, 2018, 97: 283-296.
[19] Pukthuanthong K, Roll R, Subrahmanyam A. A protocol for factor identification. The Review of Financial Studies, 2019, 32(4): 1573-1607.
[20] Bask M, Gencay R. Testing chaotic dynamics via Lyapunov exponents. Physica, D. Nonlinear phenomena, 1998(1/2): 114.
[21] Song Guanghui, Dong Yongqi, Chen Yangyang, Xu Lin. Liquidity and Momentum Effects in Chinese Stock Market - A Further Study Based on the Fama-French Five-Factor Model. Research in Financial Economics, 2017, 32(01): 36-50.
[22] Li Shuangqi, Chen Qian and Zhu Sha. Asset pricing in stock market considering consumption and investor sentiment. Journal of Management Science. 2021, 24(04).

[23] Zhang Shaohua, and Chen Huiling. Is Total Factor Productivity an Effective Capital Asset Pricing Factor? --A Fama-French factor model test based on the Chinese stock market. China Economic Issues, 2021(02): 125-140.

[24] Lintner J. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. The Review of Economics and Statistics, 1965, 47(1): 13-37.