A Quantitative Strategy for value investing in Small Cap Stocks Based on Positive Feedback Asymmetry

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Abstract. Significant positive feedback trading exists in the Chinese market, and there is a significant difference between the extent of chasing up and killing down in the context of positive feedback trading. The purpose of this paper is to investigate whether a quantitative investment strategy with this asymmetric trait as the core factor can achieve significant excess returns and reduce the risk impact of irrational investors in the market. This paper is based on the CSI 500 index represented by small-cap stocks as the strategic stock pool, and further constructs a quantitative stock selection strategy, which firstly estimates the positive feedback trading asymmetry index of individual stocks in the market through the framework of SW, and at the same time, combines the Chinese three-factor model with Amihud's illiquidity index to construct the factor portfolios, and conducts a validity test to ultimately select the four portfolios with the highest cumulative returns as factor portfolios. This paper concludes that the strategy has a return of 316.73% during the back testing period, a weekly Sharpe ratio of 0.33, and a maximum backtest of 36.41%, realizing a significant excess return with controlled risk.

Keywords: asset pricing, positive feedback trading, multi-factor modeling, yield forecasting.

1. Introduction

There are a large number of retail traders in the Chinese market. The behavior of retail traders can be viewed as positive feedback trading. Positive feedback trading refers to the strategy of following the market trend without relying on the fundamental value of the stock, buying stocks when the market is rising and selling stocks when the market is falling. Positive feedback trading reflects the trading sentiment of retail investors, especially during market volatility, and this sentiment-driven behavior has a significant amplifying effect on stock prices.

Positive feedback trading can have a significant impact on stock returns. A large number of positive feedback trades make the stock price deviate from its original value, causing serial correlation in stock returns. At the same time, positive feedback trading intensity is asymmetric in the direction about the rise and fall. In the Chinese market, investors are more willing to follow the trend and buy in large quantities when the market is rising; while the trading volume in the market is smaller relative to the rising range when the market is falling due to the disposition effect of retail investors and the restriction on short selling. This positive feedback trading uncertainty is a measure of retail investors' trading sentiment and can be used as a pricing factor to significantly explain stock returns in the cross-section.

Traditional studies of stock returns in the cross-section market capitalization, book-to-market ratio, and illiquidity. The factors constructed by these studies can all play a role in explaining stock returns in the cross-section.

Fama and French stated that market capitalization as a size factor significantly explains the returns on a cross-section of stocks and that small market capitalization stocks are more likely to have significant returns relative to large market capitalization stocks[1]. Positive feedback trading is unique to this study in the Chinese market. Although Fama and French's three-factor model is widely used in the international market, in the Chinese market, this model has limitations in explaining stock returns due to the high proportion of retail trading.

Therefore, this paper selects the constituents of the CSI 500 index represented by small-cap stocks in the Chinese market as the pool of stocks for the strategy, and constructs a quantitative strategy focusing on positive feedback asymmetry to capture the investment sentiment of irrational investors in small-cap stocks, avoid the idiosyncratic risk brought by them, and ultimately realize significant excess returns. In this paper, we firstly estimate the positive feedback trading asymmetry indicators of individual stocks in the market through the framework of SW [2]. At the same time, we combine the Chinese three-factor model with Amihud illiquidity indicators to construct factor portfolios. Secondly, we test the return effects of the four factors and select the portfolios with the highest cumulative returns of the four factors to construct the strategy. Finally, through the computation of the risk exposures of individual stocks to the factor portfolios and the weekly cumulative return prediction, we select the top 10% portfolios with the highest predicted returns. Finally, by calculating the risk exposure of the stocks to the factor portfolios and predicting the weekly cumulative returns, the top 10% stocks with the highest predicted returns will be selected as the stock pool for our strategy.

2. Literature Review

2.1. positive feedback transaction

Positive feedback traders in the market can lead to increased autocorrelation and volatility of returns, causing stock prices to deviate from their fundamental values, triggering speculative bubbles and eventually converging back due to the intervention of rational investors [3].

Positive feedback trading affects the autocorrelation and volatility of stock's return.Sentana and Wadhani constructed a market model that includes rational and positive feedback investors in their study [2]. Their empirical results show that when there are positive feedback investors in the market, the sequence of returns will show autocorrelation. DeLong [4] in his study pointed out that the presence of a large number of positive feedback traders can lead to the deviation of stock prices from their normal values, making stock returns unstable, which in turn exacerbates the volatility of the market. Positive feedback traders in the market will lead to increased autocorrelation and volatility in returns, causing stock prices to deviate from their fundamental values, triggering speculative bubbles that eventually tend to return due to the intervention of rational investors

Positive feedback trading will lead to speculative bubbles in the market, Hirshleifer et al. show that early positive feedback trading will lead to positive excess returns for investors [5]. The early rise in stock prices caused positive feedback investors to enter the market in large numbers, creating a speculative bubble in prices, but as prices deviated from their normal value, rational investors in the market traded based on the fundamental value of the stock, causing prices to revert to their original mean level.

There is an asymmetry in the intensity of positive feedback trading regarding the direction of returns, which represents the trading intensity of retail investors. Wan et al. based on the theory of Sentana and Wadhani while discussing the heterogeneity of positive feedback investor concepts[6], showed that there is significant positive feedback trading in the Chinese market and that the intensity of chasing the bulls is greater than that of the kills, and points out that this is related to the presence of a large number of retail investors in the Chinese market.

The asymmetry of positive feedback trading affects stock returns. Wan and Yang use a nonparametric approach to construct an indicator for the asymmetry of uptrend strength and discuss the pricing power of uptrend strength asymmetry [7], and find that it has significant returns in the cross-section and is different from traditional risk factors such as reversal. Wan and Liu further analyze the effect of uptrend strength asymmetry strength on future returns, and find that stocks with lower asymmetric strengths have higher returns, and suggest that this is related to the underreaction of prices due to low retail participation, resulting in price drift.

Taken together, the above studies lead to the conclusion that positive feedback trading is prevalent in the market and influences stock prices, and that its asymmetric strength with respect to the direction of returns can be used as a pricing factor to explain returns in the cross-section of stocks. Therefore, in this paper, we will construct and test a combination of factors based on positive feedback trading asymmetry, which will ultimately form our stock selection strategy.

2.2. Asset Pricing and Multi-Factor Modeling

Traditionally, asset pricing problems have been approached under the mean-variance model proposed by Markowitz based on reconciling risk and return. Sharp and Lintner proposed the CAPM model under the mean-variance framework [8] [9].

In the field of asset pricing, although the traditional CAPM model has played an important role in explaining stock returns, with the development of empirical studies, it has limitations in explaining cross-sectional returns on assets. For this reason, Fama and French constructed the classical three-factor model by adding the firm market capitalization factor (SIZE) and the book-to-market ratio factor (BM) to the CAPM [1], expanding the model's ability to explain market anomalies. Liu, on the basis of the three-factor model, proposes the existence of shell value contamination in Chinese listed companies, excludes listed companies with market capitalization in the bottom 30% quartile, and uses E/P to construct the value factor, which forms a three-factor model that is more in line with the Chinese market [10].

At the same time, liquidity also has a significant impact on stock returns in the cross-section. The earliest research on the relationship between liquidity and returns was conducted by Amihud and Mendelson, who used bid-ask spreads to measure the level of illiquidity, and empirically found that there is a positive correlation between the expected return on individual stocks and illiquidity in the U.S. stock market. Amihud empirically examined the relationship between the trading volume and the asset price, and put forward the concept of illiquidity indicator. measure as a concept, and the results of the study show that assets with high values of illiquidity indicators also have relatively high returns [11].

Combining the above studies, it can be found that, on the one hand, the previous researchers can better portray the explanatory power of the company's characteristics on the stock returns through the fundamental indicators; on the other hand, the above literature on asset pricing mainly focuses on focusing on the longer-term frequency of the financial indicators at the company level and pays less attention to the factors at the shorter-term trading level. Therefore, this paper completes the screening of the stock pool through a factor portfolio construction strategy based on fundamental size and value, combined with liquidity and short-term positive feedback trading asymmetry.

3. Data and Methodology

3.1. Data Resource

All the data selected in this paper are obtained from the CSMAR database (https://www.csmar.com). In this paper, the constituent stock data of CSI 500 in the last 5 years are selected as the optional stock pool for the strategy, and the stock trading data is from January 1, 2006 to January 1, 2022, with a total of 192 trading months. The data includes stocks' daily frequency returns (calculated as closing price/previous day's closing price-1), closing market capitalization, PE, Amihud illiquidity (derived from CSMAR-calculated data), realized volatility of individual stocks, and daily returns of the CSI 500. We exclude stocks with missing values of individual stock daily returns data greater than their tertile points, resulting in 982 stocks with 381,980 sample observations. The descriptive statistics of the data are shown in Table 1. The table shows that the volatility of individual stock returns (3.072) is greater than that of the index (1.923), and the maximum value of realized volatility is 11,810.45 while the minimum value is 0, which indicates that there is a large gap in the volatility of individual stocks between trading days.

Table 1. Statistical descriptive table of data

Statistical characteristic	Index return(%)	Daily return (%)	Closing Market Capitalization (million)	PE	ILLIQ	Realized Volatility
Minimum	-8.95	-68.733	4906.8	0.524	0.0000	0.0000
Q1	-0.75	-1.272	216888.97	21.579	0.0139	2.7820
Median	0.21	0.000	430728.99	42.836	0.0344	5.4478
Mean	0.074	0.085	1155398.06	125.343	0.3081	9.7019
Q3	1.11	1.404	916767.25	103.626	0.0917	11.3154
Maximum	9.87	917.391	278624700	22529.5	9355.04	11810.45
St.Dev	1.923	3.072	4531927.26	337.813	23.971	14.9662

The statistical description of the data for the estimated AFTs is shown in Table 2, and the t-tests for the AFTs, all of which have p-values almost equal to 0, indicate that there is a significant asymmetry of positive feedback trading in the Chinese market.

Table 2. Descriptive table of AFT indicators

Statistical characteristic	AFT
Minimum	-0.1631
Q1	-0.00217
Median	0.001362
Mean	0.001635
Q3	0.004916
Maximum	0.399686
St.Dev	0.012178

3.2. Methodology

3.2.1. Construction of positive feedback asymmetric factors

This paper estimates the degree of positive feedback asymmetry present in the market based on the framework in Sentana and Wadhani. The share of positive feedback investors is denoted as:

$$Y_t = \gamma r_{t-1} + \gamma_1 I\{r_{t-1} > 0\} r_{t-1} \tag{1}$$

Where r_{t-1} represents the return in the previous period; $I\{r_{t-1} > 0\}$ is an indicator function of the return in the previous period, which takes 1 when $r_{t-1} > 0$ and vice versa 0. Meanwhile, $\gamma > 0$ represents the existence of positive feedback trading, and if $\gamma_1 > 0$ then it represents that there is a preference for rising returns in positive feedback trading. And since the market share of rational investors is affected by risk premium under the framework assumption of SW and assuming that risk premium is a linear function on volatility, it can be obtained that

$$E_{t-1}(r_t) - \alpha = a - a\gamma r_{t-1} + b\sigma_t^2 - b\gamma\sigma_t^2 r_{t-1} - a\gamma_1 I\{r_{t-1} > 0\} r_{t-1} - \gamma_1 b\sigma_t^2 I\{r_{t-1} > 0\} r_{t-1} \tag{2}$$

Let $\beta_1 = -a\gamma, \beta_2 = b, \beta_3 = -b\gamma, \beta_4 = -a\gamma_1, \beta_5 = -\gamma_1 b$, where σ_t^2 is obtained by estimating the realized volatility, RV, in period T-1. Where feedback traders' preference for chasing up is greater than killing down, γ_1 should be greater than 0, and then β_5 should be less than 0. Therefore, we denote $-\beta_5$ as the asymmetric strength of trading AFT by estimating Equation (2).

3.2.2. Chinese triple factor

This paper constructs a three-factor portfolio for China based on the framework of Liu et al. [10]. Stocks with market capitalization in the bottom 30% are excluded from the construction of the factors due to shell contamination, a practice that allows it to explain most of the anomalies in the Chinese market. Meanwhile, PE as a value factor has the most significant explanatory power for cross-sectional returns in the Chinese market. Therefore, this paper includes the market capitalization and PE of individual stocks in the CSI 500 stock pool into the factor pool.

3.2.3. ILLIQ

Amihud in his study constructed the Amihud illiquidity indicator, which measures the liquidity of the market in terms of the absolute value of the daily return of individual stocks with the amount of turnover, and introduced it into the Fama-French three-factor model, and found that the market return of the stock is significantly and positively correlated with illiquidity. In this regard, the methodology of constructing Amihud illiquidity indicator is shown below [11]:

$$ILLIQ_{im} = 10^{10} \times \frac{1}{D_{im}} \sum_{t=1}^{D_{iy}} \frac{|R_{imd}|}{VOLD_{imd}} \tag{3}$$

Where R_{imd} is the daily return of the stock in month m, D_{im} is the number of trading days of the stock in that month m, and $VOLD_{imd}$ is the daily volume of the stock in month m.

3.2.4. Strategy building methodology

The first step is to calculate the risk exposure of individual stocks on the factor portfolios. In this paper, we select every 5 trading days as the position changing cycle, in the position changing day we construct regression (4) based on the data of the past 500 trading days of individual stocks, respectively, to find the regression coefficient of the daily frequency return of individual stocks on the factor portfolio return, and get the factor exposure $\beta_1, \beta_2, \beta_3, \beta_4$ of the past 250 trading days.

$$RE_i = \beta_0 + \beta_1 SIZE_L + \beta_2 ILLIQ_4 + \beta_3 PE_2 + \beta_4 AFT_L + u \tag{4}$$

In the second step, the return prediction model is constructed. In this paper, we first calculate the cumulative return WRE_i of individual stocks for the past week on a every five trading day basis.Then, based on the factor exposures for the past 250 trading days, we construct the regression model (5), which fits the WRE_i for the past year to obtain the model parameters for the current week.

$$WRE_i = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \gamma_3\beta_3 + \gamma_4\beta_4 + u \tag{5}$$

In the third step, the cumulative return for the coming week is predicted. Based on the model parameters obtained from the above fitting, we input the factor exposure coefficients for the current week into model (5) to obtain the predicted value of WRE_i of the current week.

In the fourth step, the final stock pool of the strategy is selected. In this paper, based on the predicted returns obtained in step 3, we take out the stocks with predicted returns WRE_i ranked in the top 10% and weight the portfolio according to the closing market capitalization of the previous day to obtain the final stock pool of the strategy.

4. Results

In this section, the significance of the different factors in the returns will be assessed by the Newey-West test to determine their validity. At the end of each month, the stocks are divided into five groups, L,2,3,4,H, based on each of the four factors, from smallest to largest in terms of percentile points (Table 3 and Table 4):

Table 3. Newey-West group test matrix for each factor

	L	2	3	4	H	MINUS
AFT	0.0914***	0.0586**	0.0524*	0.0665**	0.0674**	0.0239*
	[0.0284]	[0.0297]	[0.0303]	[0.0304]	[0.0307]	[0.0145]
ILLIQ	0.0536*	0.0684**	0.0740**	0.0908***	0.0702**	0.0166
	[0.0283]	[0.0335]	[0.0325]	[0.0308]	[0.0305]	[0.0194]
PE	0.0693***	0.0888***	0.0759***	0.0564*	0.0458	0.0235
	[0.0276]	[0.0297]	[0.0300]	[0.0336]	[0.0358]	[0.0234]
SIZE	0.1260***	0.1131***	0.0768**	0.0680**	0.0572**	0.0689***
	[0.0369]	[0.0343]	[0.0346]	[0.0336]	[0.0278]	[0.0256]

Note: The average return of each group is in %. Where *** represents p<0.001, ** represents p<0.05, and * stands for p<0.1

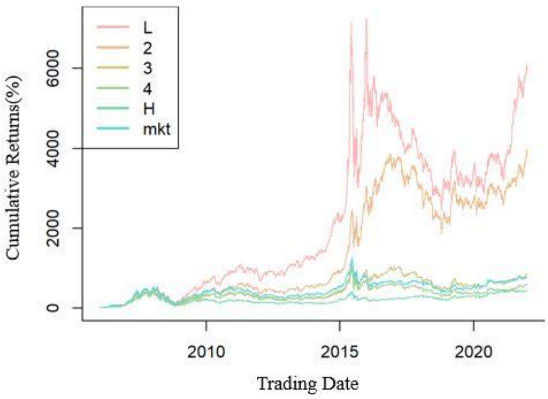
Table 4. CSI 500 market index returns Newey-West test

	Mean	Newey-West Std.
MARKET	0.0982***	0.0309

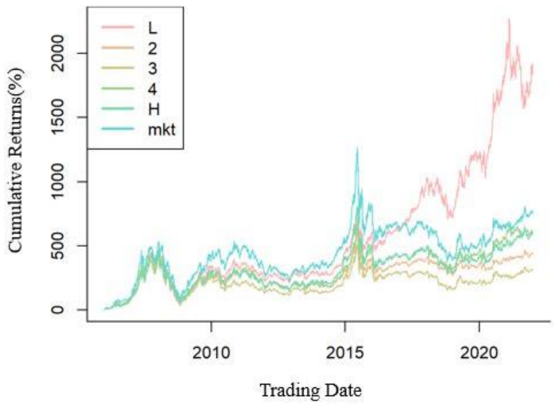
Note: where *** represents p<0.001, ** represents p<0.05, * represents p<0.1, * represents p<0.1, and * represents p<0.1., * stands for p<0.1

Where the MINUS column is the difference between the returns of group H and group L. ILLIQ refers to the grouping by Amihud illiquidity and SIZE refers to the grouping by market capitalization. It can be seen that the MINUS of factors AFT and SIZE are all significant at 10% confidence intervals, which suggests that market capitalization and positive feedback asymmetry explain to some extent the differences between stocks in the cross-section.The MINUS of PE and ILLIQ are both insignificant, but group 2 of PE and group 4 of ILLIQ, among others, both achieve significant returns at 1% confidence intervals. Meanwhile, the return of CSI 500 market index is also significant at 1% confidence interval.

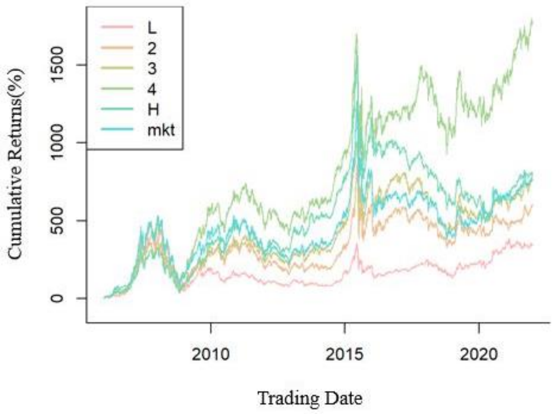
The above results indicate that the constructed portfolios are all effective in obtaining returns to some extent. Next, the cumulative returns achieved by each group during the sample period will be further examined and compared with the CSI 500 index returns, and the results are shown in Fig. 1.



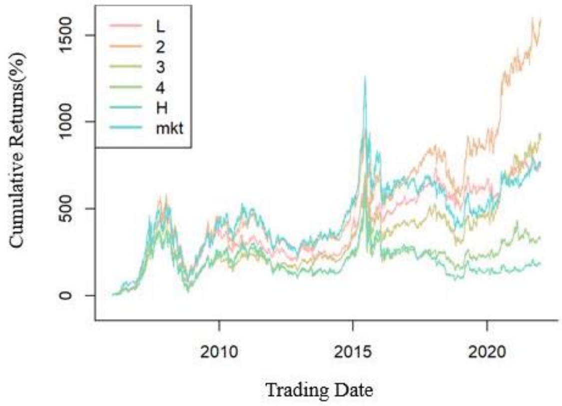
(a) Market Capitalization Grouping



(b) Positive feedback asymmetry grouping



(c) ILLIQ Grouping



(d) PE Grouping

Figure 1. Time series plot of cumulative returns of the factor portfolios

After grouping the four factors of market capitalization, positive feedback asymmetry, illiquidity and P/E ratio according to quintiles, it is found that the highest cumulative returns among them are group L for market capitalization, group 4 for Amihud's illiquidity, group 2 for PE, and group L for the positive feedback asymmetry indicator, respectively. In addition, the cumulative returns of all four factor portfolios are above the market index, achieving significant excess returns.

Therefore, in this paper, January 1, 2021 to January 1, 2022 is selected as our strategy backtesting (Fig.2):

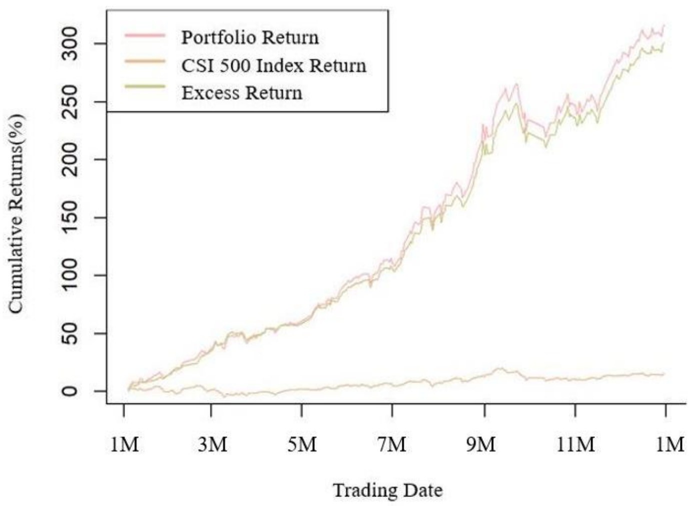


Figure 2. Strategy Backtest Cumulative Return Performance (January 1, 2021 - January 1, 2022)

Table 5. Strategy Back testing Return Performance

Strategic gain	Sharpe ratio	Maximum retracement
316.73%	0.33	36.41%

In Table 5, this paper finds that the strategy achieved significant excess returns during the backtesting period. The strategy has a Sharpe ratio of 0.33 and a maximum retracement of 36.41%, with the maximum retracement range from September 2021 to October 2021, possibly due to the increased volatility of the market environment during this period, which resulted in greater selling pressure on the small-cap and illiquid stocks in the strategy due to the lack of funding liquidity. In addition, positive feedback trading tends to exacerbate stock price declines during market downturns, especially in the retail-dominated Chinese market, resulting in a significant impact on strategy performance.

5. Discussion

5.1. Break-even analysis

The analysis reveals that the strategy achieves significant excess returns in the above backtested intervals, so the reasons for the strategy's excess returns are considered to be as follows:

First, the strategy captures the excess returns of the L group of market capitalization, the 4 group of Amihud illiquidity, the 2 group of PE, and the L group of positive feedback asymmetric indicator very well. The four factor portfolios have higher return performance in the test, and by averaging our risk exposures across the four factor portfolios, the strategy achieves more robust cumulative returns over the backtest interval.

Second, the frequency of position changes entered into the strategy is more consistent with short-term investing. The strategy chooses to change positions every five trading days, and by fitting the weekly factor exposures to the weekly cumulative returns over the past year, we are better able to capture short-term investment opportunities and achieve higher excess returns.

5.2. Directions for improvement

Although the strategy in this paper initially achieves high return performance at the stock selection level, there is still room for improvement in many dimensions.

First, this paper suggests a weighting strategy to optimize the portfolio. The current weighting of our strategy is to allocate funds according to market capitalization weighting, which does not take into account the relationship between risk and return. Therefore, in the future direction of improvement, we can try to consider incorporating it into the weight allocation method, such as using realized volatility for weight deflation, or weight adjustment based on Black Litterman model, etc.

Secondly, a timing strategy can be implemented to capitalize on market opportunities. Currently, our strategy is to fix 5 trading days to change positions and use a hold-to-maturity strategy in between the changing days. In the future, we can build a model to predict shorter-term returns based on daily trading data to make timing adjustments to the portfolio.

Third, we recommend developing position and individual stock stop-loss strategies to control risk. Currently our strategy takes a full position buy approach, in the market upward range of the full position will get considerable gains, while in the market downward range of the strategy will get a greater loss. At the same time, we can also set up a stop-loss strategy for individual stocks, such as closing out a position when it reaches a loss of 12% during the holding period.

Fourth, in the future, we can improve the forecasting method of return to increase the accuracy of investment decision. In this paper, we simply use a linear model to input the exposure parameters of risky portfolios, which can only capture linear relationships in lower dimensions, and its accuracy needs to be improved. In future improvements we can also introduce algorithms in machine learning to improve the prediction of yield and enhance the accuracy of prediction.

6. Conclusion

This study constructs a quantitative investment strategy for small-cap stocks based on the positive feedback trading asymmetry feature present in the Chinese market, aiming to capture the impact of retail investors' behavior on the market so as to achieve excess returns. The study utilizes the SW framework to estimate the positive feedback asymmetry indicators of individual stocks and combines the Chinese three-factor model with the Amihud illiquidity factor to construct an investment strategy consisting of a combination of four factors. The backtest results show that the strategy obtains significant excess returns with controlled risk: the strategy return reaches 316.73%, the weekly Sharpe ratio is 0.33, and the maximum retracement is 36.41%, suggesting that the corresponding idiosyncratic risk can be effectively avoided and the performance of the returns can be enhanced by capturing the trading sentiment of irrational investors in small-cap stocks.

This study finds that positive feedback asymmetry as a pricing factor can significantly explain the cross-sectional return differences of stocks, especially in the context of retail investors' preference for chasing up in the Chinese market, and its prediction of returns has stability and validity. Future research can further optimize the weight allocation method based on this strategy, such as using realized volatility or machine learning algorithms to improve the accuracy of return prediction. In addition, a time-timing mechanism and stop-loss strategy can be introduced to better control risk during market volatility. This study provides new perspectives for the development of quantitative investment strategies, especially in the market where retail investors are active, and helps to balance return and risk more effectively through a deeper understanding of their trading patterns.

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