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# Can Intraday Return Reversals Predict Future Stock Returns?

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**Abstract:** Based on the research of the US stock market, it is found that the fierce long-short battle between heterogeneous investors with different views is manifested as the high-frequency inversion between overnight returns and daytime returns over a period of time. This kind of long-short battle has an impact on asset prices over time, resulting in pricing anomaly on a cross-section. Based on the research of A-share market, this paper finds that after controlling the characteristics of scale, book-to-market ratio, reversal effect, profitability, turnover rate, etc., the abnormal frequency of opening high and closing low (AB_NR) is significantly positively correlated with the future return of stocks. The hedge portfolio constructed according to AB_NR has excess returns in time series (opening high and closing low anomaly) which cannot be explained by the existing asset pricing model. Further testing shows that the anomaly is significant in the period of high arbitrage cost and high investor sentiment. The empirical results show that the anomaly is due to mispricing rather than risk premium.

**Keywords:** Asset Pricing Anomaly, Mispricing, Heterogeneous Investors.

## 1. Introduction

Since the establishment of Shanghai Stock Exchange and Shenzhen Stock Exchange at the end of 1990, China's securities market has experienced more than 30 years of continuous development and growth. By the end of 2023, there are 5,107 listed companies in Shanghai and Shenzhen, with A total market value of 77.31 trillion yuan, among which 3,197 A-shares on the main board of Shanghai and Shenzhen, with a total market value of 59.65 trillion yuan. According to the World Federation of Exchanges (WFE) and Securities Industry and Financial Markets Association (SIFMA) global stock market capitalization and share data for the second quarter of 2023, the Chinese stock market ranks third in the world with a total market capitalization of $11.5 trillion, accounting for 10.6% of the global stock market share.

However, due to the late start and insufficient development of China's stock market, there are outstanding problems such as unreasonable investor structure at this stage, which makes the overall asset pricing efficiency of the stock market not high enough and financial anomalies appear frequently. First of all, the structure of investors in China's stock market is unreasonable, which is manifested in the large number of individual investors, the proportion of shareholding and the proportion of transactions are high, which is significantly different from the dominant position of institutional investors in mature markets such as the US stock market. Second, individual investors are limited rational, the ability to distinguish between noise and information is not strong, investment behavior may be based on noise rather than information itself, resulting in noise investor risk, and then have an impact on asset prices. Finally, compared with professional institutional investors, individual investors have relatively simple information access channels, which makes it difficult to obtain timely and effective information, easy to ignore changes in the company's fundamentals, and often have insufficient response to information. At the same time, when individual investors choose stocks, the speculative atmosphere is strong, and the degree of irrationality is high, with the following characteristics: keen to follow the trend of chasing hot spots, chasing small caps and chasing short frequency trading, which is related to individual investors' superstitious gossip, overconfidence psychology, and susceptibility to market sentiment, resulting in overreaction investment behavior. In essence, both under-reaction and over-reaction will cause stock prices to deviate from their intrinsic value, lead to mispricing, reduce asset pricing efficiency, and lead to financial market anomalies. Asset pricing efficiency is related to the efficiency of capital market resource allocation. In the context of the current economic transformation in China, it is necessary to make use of the advantages of capital market risk pricing and resource allocation to help industrial upgrading and scientific and technological innovation, research on asset pricing and financial anomalies is particularly necessary.

Recently, based on the study of the long-short competition in the American stock market, it is found that the overnight return daytime reversal frequency has the ability to predict stock returns in a cross-section, and then a new asset pricing anomaly in the American stock market is discovered [1] [2]. Lou et al. (2019) [1] proposed that individual investors and institutional investors tend to dominate overnight and day trading hours respectively, and the continuous excess demand of these two types of investors may cause a "tug of war" in stock prices, resulting in the reversal of returns in overnight and day trading periods. Akbas (2022) [2] argues that the predictability of returns can be explained by the excessive correction of positive overnight returns by daytime arbitrageurs, that is, daytime arbitrageurs overestimate the role of noise traders behind the pressure of high opening prices, and may overlook that continuous positive overnight returns may be due to positive information leading to improved fundamentals, rather than just optimistic noise trading.

However, the existing overnight return day inversion has the ability to predict future returns in the cross section mainly for the mature US stock market, and there are few studies on emerging markets, especially the Chinese A-share market. Since the Chinese and American stock markets differ greatly in terms of market trading mechanism and investor structure, whether the relevant research conclusions are applicable to China's A-share market remains to be verified. The purpose of this paper is to explore whether there are similar cross-sectional pricing anomalies in China's A-share market, and to further analyze whether the anomalies are caused by risk compensation or mispricing.

# 2. Literature Review

Abundant existing studies have shown that heterogeneous beliefs and heterogeneous investors can have a significant impact on asset prices[3][4][5]. In the real capital market, the traditional capital asset pricing model and the efficient market have three preconditions for homogeneous beliefs: information is free, investors get the same information at the same time, and investors are difficult to meet the same information processing methods, so heterogeneous beliefs emerge. Heterogeneous beliefs were proposed by Miller (1977)[6], who believed that different investors have different expectations of expected returns, and such heterogeneous beliefs will affect asset prices. Harrison and Kreps (1978)[3] pointed out that investors have heterogeneous expectations in the real world. Some investors buy stocks mainly for the purpose of speculation rather than high intrinsic value, believing that they can sell stocks to others at a higher price in the future, and such expectations will lead to the formation of price bubbles.

Heterogeneous investors can be divided into insiders and outsiders according to whether they have inside information. It can be divided into long-term investors and short-term investors according to the length of holding time. According to the scale of funds, professional level can be divided into individual investors and institutional investors. De Long et al. (1990)[7] proposed the noise trading model (DSSW), which divides heterogeneous investors into two types: irrational noise traders and rational arbitrageur based on information trading. It believes that the existence of noise traders will cause asset prices to deviate from intrinsic value, and rational information traders will face the risk of noise traders. This risk will encourage information traders to participate in the directional trading of noise traders, and the trading activities of the two types of investors together affect the stock price. Lou et al. [1] believes that individual investors, corresponding to noise traders, tend to collect information and make decisions overnight, while institutional investors, corresponding to rational arbitrageurs, tend to make reverse operations during the day. Due to factors such as cognitive bias and limited attention, individual investors are regarded as irrational people, and their ability to obtain information and analyze information is relatively poor, unable to timely and accurately capture new information, and trading is more based on noise rather than information itself. The degree of confidence in their own judgment is higher than the degree of accuracy, showing overconfidence; Personal ideas and investment behaviors are easily influenced by market environment and other investors, showing herd effect [8]. When trading stocks, the tendency to sell the profitable stocks too early and continue to hold the losing stocks has a significant disposal effect [9]. Institutional investors have a high degree of professionalism, rich experience in investment practice, and significant information advantages. They are often regarded as informed traders who are more rational in trading behavior and generally trade based on fundamentals. Therefore, the differences in investment philosophy, trading behavior, information advantages and other aspects cause individual investors and institutional investors to form heterogeneous beliefs, which will affect the formation of asset prices.

# 3. Data, Variables, And Descriptive Statistics

## 3.1. Data and sample

The research object of this paper is A-share listed companies from 2006 to 2022, and the original data are screened according to the following criteria: (1) The stocks with delisting risk warning (i.e., the special treatment of ST and *ST) are excluded; (2) Excluding financial and insurance listed companies; (3) Excluding new shares within one year of listing. The final sample contains 309,322 monthly observations from companies.

The data in this paper mainly includes trading data and financial data of listed companies, both of which come from CSMAR database. In terms of trading data: the opening and closing prices of individual stocks are adopted after the resumption price, and the monthly return rate is selected to consider the return rate of dividend reinvestment. Financial data: Data mainly comes from financial statements. In order to avoid data foresight bias, this paper stipulates that the financial data of listed companies in year T should be obtained from the financial statements of year T-1, and the financial data should be further backmatched to form monthly data. In addition, all continuous variables were Winsorize to avoid the interference of outliers on the empirical analysis results.

## 3.2. Variables

The core explanatory variables of this paper are two indicators based on the overnight and daytime returns of individual stocks, namely, the change of monthly opening high and closing low frequency of individual stocks compared with the average level in the past 12 months (AB_NR) and the change of opening low and closing high frequency compared with the average level in the past 12 months (AB_PR). The specific construction method is as follows: First, referring to the practice of Akbas (2022) [2], the daily return (Retid) of individual stock i on the trading day d is decomposed into two parts: overnight return (Ret_nightid) and daytime return (Ret_dayid). The daytime yield is calculated by the opening price (Popenid) and closing price (Pcloseid) of the trading day, and the calculation formula is:

$$\text{Ret\_day}_{id} = \frac{P_{id}^{Close}}{P_{id}^{Open}} - 1 \tag{1}$$

In the calculation of overnight return rate, considering that stock splitting and other behaviors may affect it, this paper uses daily return rate (Retid) and daytime return rate (Ret_dayid) to derive the calculation formula as follows:

$$\text{Ret\_night}_{id} = \frac{1 + Ret_{id}}{1 + \text{Ret\_day}_{id}} - 1 \tag{2}$$

If the overnight return is greater than zero ($\text{Ret\_night}_{id}>0$) and the daytime return is less than zero ($\text{Ret\_day}_{id}<0$), it is defined as opening high and closing low. If the overnight return rate is less than zero ($\text{Ret\_night}_{id}<0$) and the daytime return rate is greater than zero ($\text{Ret\_day}_{id}>0$), it is defined as opening low and closing high. The monthly frequency of opening high and closing low (opening low and closing high) is obtained through the proportion of the days of opening high and closing low (opening low and closing high) in the trading days of t month, which is recorded as $NR_{it}$ ($PR_{it}$). These two frequency indicators reflect the intensity of the long-short duel of stock i in t month, and the long-short duel becomes more intense with the increase of $NR_{it}$ ($PR_{it}$). Finally, the core variable of this paper is the monthly frequency of abnormal opening high and closing low (opening low and closing high), which is denoted as $AB\_NR_{it}$ ($AB\_PR_{it}$), which is obtained by the ratio of intra-day return reversal frequency in t month to the average of monthly return reversal frequency in the previous 12 months, and the calculation formula is as follows:

$$AB\_NR_{it} = \frac{NR_{it}}{1/_{12}\sum_{j=1}^{12} NR_{it-j}} \tag{3}$$

$$AB\_PR_{it} = \frac{PR_{it}}{1/_{12}\sum_{j=1}^{12} PR_{it-j}} \tag{4}$$

In terms of control variables, based on the existing research and combined with the actual situation of the A-share market, this paper selects the following indicators as control variables: (1) Size: the total market value of stocks at the end of the month, which is used to control the size of the company. (2) BM: book-to-market ratio. Book value adopts the net asset data of last year's financial report to match the corresponding month, and market value adopts the total market value of stocks at the end of the month (Size). (3) Ret: the return rate of the stock that considers the cash dividend reinvested in the month, which is used to control the short-term reversal effect. (4) Ret112: Cumulative stock return over the previous 1 to 12 months, used to control the medium-term momentum effect. (5) Turn: turnover rate, monthly average of the daily turnover rate. (6) Agt: the growth rate of total assets is used to control the investment effect of the company. (7) GP: Gross profit rate, using the method defined by Novy-Mark (2013)[10], where the numerator is operating income minus operating cost and the denominator is total assets. (8) Illiq: illiquidity index. First, the absolute daily return of individual stocks is calculated divided by the daily transaction amount, and then the monthly average is further calculated. (9) IVOL: idiosyncrasic volatility. First, the daily rate of return of individual stocks was used to conduct Fama-French three-factor model regression, and then the sample standard deviation of regression residual was used to obtain the monthly idiosyncrasic volatility of individual stocks. (10) IO: proportion of shares held by institutional investors.

### 3.3. Descriptive statistics

**Table 1.** Summary statistics for main variables

| | Mean | STD | MIN | MEDIAN | MAX |
|---|---|---|---|---|---|
| AB_NR | 1.0247 | 0.4462 | 0.0092 | 0.9898 | 3.0553 |
| AB_PR | 1.0080 | 0.3594 | 0.0731 | 0.9844 | 2.5466 |
| NR | 0.2200 | 0.0925 | 0.0024 | 0.2165 | 0.5701 |
| PR | 0.2937 | 0.1020 | 0.0224 | 0.2889 | 0.6803 |
| Size | 22.5083 | 0.9320 | 21.0002 | 22.3389 | 25.4247 |
| BM | 0.4566 | 0.2859 | 0.0727 | 0.3904 | 1.5469 |
| Ret | 0.0171 | 0.0983 | -0.1795 | 0.0032 | 0.3595 |
| Ret112 | 0.2136 | 0.3212 | -0.4074 | 0.1700 | 1.2298 |
| Turn | 1.693 | 1.2843 | 0.1858 | 1.3550 | 7.1029 |
| GP | 0.2851 | 0.1695 | 0.0363 | 0.2467 | 0.8194 |
| Agt | 0.0904 | 0.1452 | -0.1651 | 0.0591 | 0.7700 |
| Illiq | 0.0581 | 0.0488 | 0.0033 | 0.0441 | 0.2411 |
| IVOL | 0.0938 | 0.0368 | 0.0336 | 0.0881 | 0.2035 |

Note: In empirical asset pricing, descriptive statistics are calculated in two steps. The first step: calculate cross-section statistics, and obtain descriptive statistics for all stocks in each period; Step 2: Calculate the mean of the time series on the basis of the sectional average statistics.

Table 1 shows the time series averages of the variables in the monthly cross-sectional summary statistics. Firstly, it is noted that the average monthly opening high and closing low frequency of NR is 22.00%, and on average, there are about 5 trading days each month with opening high and closing low. The average monthly low opening high frequency PR is 29.37%, indicating that the frequency of low opening high is higher than that of high opening low. This may be related to the "T+1" trading system of the A-share market, that is, only the stocks sold at the opening of the day are allowed to be bought, but the stocks bought on the day are not allowed to be sold. Therefore, the opening buyers of stocks require price compensation for the decline in liquidity. As A result, the average overnight return of A-shares is negative [11]. Secondly, it is noted that the AB_NR mean is close to 1, which indicates that the monthly high open low frequency NR is very close to its moving average over the past 12 months. However, AB_NR has a very significant variation from the minimum value of 0.0092 to the maximum value of 3.0553, indicating that the amplitude of the negative high-on-low frequency is larger. AB_PR is similar to AB_NR in that the mean value is around 1 and the value also has a large amplitude.

## 4. Main Analysis: Intraday Return Reversals and Future Stock Returns

### 4.1. Fama-Macbeth regression approach

In this paper, Fama-Macbeth cross-sectional regression method is adopted to explore the impact of AB_NR and AB_PR on the future stock returns on the cross-sectional basis under the control of multiple variables. The explained variable is the monthly return rate of the next month, and the core explanatory variables are AB_NR and AB_PR. The control variables are market capitalization Size (Size), book-to-market ratio (BM), short-term momentum (Ret), medium-term momentum (Ret112), turnover rate (Turn), gross profit margin (GP), total asset growth rate (Agt), and institutional investor shareholding ratio (IO). In order to obtain robust regression results, the regression equation is set differently, and its basic form is as follows:

$$Ret_{it+1} = \beta_0 + \beta_1 AB\_NR_{it} + \beta_2 AB\_PR_{it} + \beta_3 Size_{it} + \beta_4 BM_{it} + \beta_5 Ret_{it} + \beta_6 Ret112_{it} + \beta_7 Turn_{it} + \beta_8 Agt_{it} + \beta_9 GP_{it} + \beta_{10} Illiq_{it} + \beta_{11} IVOL_{it} + \beta_{12} IO_{it} + \varepsilon_{it} \quad (5)$$

Where i represents individual; t stands for month; β0 represents the intercept term; β1 and β2 represent the regression coefficients of the core explanatory variables AB_NR and AB_PR respectively, β3-12 represents the regression coefficients of each control variable, and ε represents the residual term.

**Table 2.** Fama-Macbeth regression results

| Dependent | (1)Ret_t+1 | (2)Ret_t+1 | (3)Ret_t+1 | (4)Ret_t+1 | (5)Ret_t+1 |
|---|---|---|---|---|---|
| AB_NR | 0.0023*** | 0.0033*** | 0.0021*** | 0.0021*** | 0.0015*** |
| | (2.95) | (5.23) | (3.58) | (3.72) | (2.72) |
| AB_PR | -0.0032** | -0.0027** | 0.0005 | 0.0004 | 0.0014 |
| | (-2.35) | (-2.14) | (0.44) | (0.34) | (1.31) |
| Size | | -0.0049*** | -0.0047*** | -0.0048*** | -0.0052*** |
| | | (-3.20) | (-2.98) | (-3.13) | (-3.51) |
| BM | | 0.0070* | 0.0033 | 0.0043 | 0.0008 |
| | | (1.69) | (0.86) | (1.20) | (0.22) |
| Ret | | | -0.0488*** | -0.0493*** | -0.0220** |
| | | | (-6.16) | (-6.33) | (-2.55) |
| Ret112 | | | -0.0003 | -0.0003 | 0.0071** |
| | | | (-0.10) | (-0.13) | (2.57) |
| GP | | | | 0.0057 | 0.0028 |
| | | | | (1.55) | (0.81) |
| Agt | | | | 0.0025 | 0.0015 |
| | | | | (1.17) | (0.74) |
| Turn | | | | | -0.0040*** |
| | | | | | (-5.33) |
| Illiq | | | | | 0.1097*** |
| | | | | | (2.82) |
| IVOL | | | | | -0.0909*** |
| | | | | | (-4.96) |
| IO | | | | | 0.0000* |
| | | | | | (1.69) |
| N | 309322 | 309322 | 309322 | 309322 | 309322 |
| R^2 | 0.0058 | 0.0537 | 0.0764 | 0.0833 | 0.1045 |

Note: *, **, *** indicates significant at 10%, 5%, 1% levels. The t-value was adjusted by Newey-West lag for 4 periods

As can be seen from Table 2, in forms (1) to (5), although the set of control variables is constantly changing, the coefficients of AB_NR are significantly positive and relatively stable, indicating that AB_NR has a significant positive relationship with the monthly income in the future period. However, AB_PR coefficient is significantly negative only in forms (1) and (2), and with the gradual increase of control variables, AB_PR coefficient is no longer significantly negative, indicating that the abnormal frequency of monthly opening high and closing low of individual stocks cannot effectively predict the future return of stocks. Therefore, the following research in this paper will not examine the relationship between AB_PR and future stock returns. In addition, we also find that the coefficient of BM is not significant in forms (2) ~ (5), indicating that there is no significant book-to-market effect in the A-share market. The coefficient of Ret is significantly negative, indicating that the short-term performance of the A-share market is A significant reversal effect. The Turn coefficient is significantly negative, indicating that the turnover rate has a significant negative impact on the stock return rate.

## 4.2. Building asset portfolios

As a non-parametric technical analysis method, combinatorial analysis does not depend on a specific function form or distribution hypothesis, which helps to reveal the nonlinear relationship between variables that are difficult to be tested by parametric method. It is widely used in the field of empirical asset pricing, especially in the study of the complex relationship between multiple variables of cross-sectional data. In this section, univariate grouping and bivariate grouping test methods are used respectively to construct investment portfolios according to AB_NR to explore whether there is an anomaly of opening high and closing low in the A-share market.

### 4.2.1. Portfolio sort test

At the end of each month, all the stocks in the sample are divided into 10 groups according to the AB_NR value from small to large, and equal weight allocation is carried out within each group, with a holding period of 1 month. Build a long/short portfolio by going long the portfolio with the largest AB_NR value and short the portfolio with the smallest AB_NR value. In a long-short portfolio, the funds of the long and short portfolios are the same, that is, the funds are neutral. Based on the grouping results, the average returns of 10 portfolios and long-short hedge portfolios were calculated respectively, as well as the risk-factor adjusted returns obtained after regression of the time series of these 10 portfolios with the CAPM model and Fama-French three-factor model. The results are shown in Table 3 below:

**Table 3.** Equal-weighted portfolio returns

| AB_NR | Raw return | t | CAPM$\alpha$ | t | FF3$\alpha$ | t |
|---|---|---|---|---|---|---|
| L | 1.369 | 1.76 | 1.007 | 1.54 | 1.077 | 1.67 |
| 2 | 1.667 | 2.18 | 1.316 | 2.01 | 1.333 | 2.08 |
| 3 | 1.757 | 2.34 | 1.417 | 2.21 | 1.490 | 2.35 |
| 4 | 1.866 | 2.39 | 1.493 | 2.29 | 1.560 | 2.45 |
| 5 | 1.841 | 2.33 | 1.474 | 2.22 | 1.537 | 2.39 |
| 6 | 1.892 | 2.49 | 1.509 | 2.41 | 1.547 | 2.54 |
| 7 | 1.867 | 2.50 | 1.508 | 2.39 | 1.579 | 2.56 |
| 8 | 2.012 | 2.53 | 1.631 | 2.43 | 1.710 | 2.64 |
| 9 | 1.810 | 2.47 | 1.467 | 2.32 | 1.573 | 2.53 |
| H | 1.999 | 2.58 | 1.616 | 2.51 | 1.711 | 2.69 |
| H-L | 0.631*** | 4.16 | 0.609*** | 4.00 | 0.634*** | 3.99 |

As can be seen from Table 3, the average portfolio return on the whole increases with the increase of AB_NR value, showing a significant positive correlation. Specifically, the average rate of return of the portfolio without risk adjustment increased from 1.37% per month in the lowest group of ABNR (Decile1) to 2.00% in the highest group (Decile10). On a monthly basis, building a fund-neutral long-short portfolio by going long the highest group of AB_NR and short the lowest group can yield an excess return of 0.63% (7.56% annualized). In this paper, the CAPM model and Fama-French three-factor model are used to adjust the portfolio return rate, and it is found that the long-short hedge portfolio can obtain a significant excess return of 0.61% and 0.63% respectively.

#### 4.2.2. Independent double sorting

This section analyzes the differences in portfolio returns under the control of different corporate characteristics. Month-end total market value (Size) was selected as the scale control factor, and book-to-market ratio (BM) was selected as the value control factor. Take the independent double ranking of AB_NR and market value (Size) as an example: From January 2006 to December 2022, all stocks are divided into 5 groups according to the 20%, 40%, 60% and 80% quantiles of AB_NR at the end of each month, which are successively Low, 2,3,4 and High groups. At the same time, the control variables are bounded by 30% and 70% quantiles according to the traditional practice, and all listed companies are divided into three groups: The Big group with market capitalization (Size) higher than 70% of the quantile, the Midden group with market capitalization (Size) between 30% and 70% of the quantile, and the Low group with market capitalization (Size) lower than 30% of the quantile, a total of 15 portfolios are obtained by the intersection of two pairs, and stocks are allocated in an equal weight manner in each portfolio. Table 4 reports the portfolio returns of AB_NR with independent double ranking of market capitalization and book to market ratio, respectively.

**Table 4.** Hedge portfolio returns based on AB_NR

| | | AB_NR | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | L | 2 | 3 | 4 | H | H-L | t |
| Size | S | 2.108 | 2.418 | 2.544 | 2.673 | 2.675 | 0.567*** | 3.98 |
| | M | 1.203 | 1.616 | 1.705 | 1.824 | 1.743 | 0.540*** | 3.95 |
| | B | 1.165 | 1.396 | 1.430 | 1.374 | 1.327 | 0.162 | 0.87 |
| BM | L | 1.012 | 1.462 | 1.667 | 1.583 | 1.644 | 0.632*** | 3.48 |
| | M | 1.509 | 1.865 | 1.916 | 2.100 | 2.069 | 0.560*** | 4.66 |
| | H | 1.965 | 2.084 | 2.017 | 2.119 | 2.063 | 0.098 | 0.84 |

As can be seen from Table 4, in the bivariate grouping results of AB_NR and Size factor (Size), the overall portfolio return rate increases with the increase of AB_NR, regardless of the size of the company. In addition, with the continuous increase of market capitalization, the excess return and significance of long-short portfolio gradually decreased, and the monthly excess return decreased from 0.57% (t-value 3.98) to 0.16% (t-value 0.87) of small market capitalization. The anomaly showed significant performance in small market capitalization and middle market capitalization. This is consistent with the characteristics that small-cap stocks are more favored by individual investors and easier to hype.

In the bivariate grouping results of AB_NR and value factor (BM), with the gradual increase of book-to-market ratio, the monthly abnormal return of long-short portfolio gradually decreases, from 0.63% (t-value 3.48) of low BM portfolio to 0.10% (t-value 0.84) of high BM portfolio. Compared with high book-to-market ratio, medium and low book-to-market ratio stocks often have poor performance at this stage, but some high-growth companies have greater potential in the future and are often favored by individual investors, although their current performance is poor.

# 5. Are Excess Returns Due to Risk Premium or Mispricing?

In this paper, the excess return obtained from the hedge portfolio constructed according to AB_NR is defined as the anomaly of opening high and closing low. Next, explore the source of the vision. As for the sources of excess returns obtained by anomaly, scholars often explain them from the perspective of risk compensation based on traditional asset pricing theory or from the perspective of mispricing based on behavioral finance theory. This section analyzes the sources from two perspectives, risk compensation and mispricing respectively.

## 5.1. Are excess returns due to a risk premium?

If a variable is predictive of future returns, it is essentially because it is a good proxy for an asset's exposure to a systemic risk. According to the traditional capital asset pricing model, a factor simulation portfolio is constructed using this variable, and the exposure of the asset to this risk is determined by the Beta value of the asset to the portfolio. Under the risk-compensated interpretation, this Beta value should be a better predictor of future yield than the variable itself. By referring to Carhart's idea (1997) [12] of building momentum factor, we sorted individual stocks according to the value of AB_NR from small to large in t month, divided all stocks into three groups by 30% and 70% quantiles, and constructed a fund neutral portfolio by going long on the group with a high AB_NR and short on the group with a low AB_NR. The return of the portfolio t+1 month is the FMI factor. Further, the regression coefficient of the FMI factor, FMI factor and Fama-French three factors of individual stock excess return is obtained, which is the FMI factor load. Finally, when the relevant characteristics are controlled, the Fama-Macbeth regression is used to test whether the expected return of stocks is significantly positively correlated with the FMI factor load. The results are shown in Table 5:

**Table 5.** Fama-Macbeth regression results after adding FMI factor loading

| | (1)Ret_t+1 | (2)Ret_t+1 | (3)Ret_t+1 |
|---|---|---|---|
| FMI | -0.00024 | -0.00011 | 0.00024 |
| | (-0.27) | (-0.13) | (0.26) |
| AB_NR | | 0.00382*** | 0.00349*** |
| | | (5.04) | (5.31) |
| Size | | -0.00493*** | -0.00620*** |
| | | (-3.42) | (-9.08) |
| BM | | 0.00694 | 0.01047*** |
| | | (1.32) | (4.39) |
| Beta | | | 0.00881 |
| | | | (1.50) |
| SMB | | | -0.00399 |
| | | | (-1.38) |
| HML | | | -0.00517* |
| | | | (-1.96) |
| N | 305314 | 305314 | 305314 |
| R^2 | 0.0208 | 0.0731 | 0.1780 |

From form (1) of Table 5, it can be seen that the regression coefficient of FMI factor load on future return rate is negative, and the t-value is a small -0.27, indicating that there is no significant linear relationship between them. After adding other factor loads and control related features (forms 2 and 3), the correlation between return rate and FMI factor load is still not significant, but the positive correlation between return rate and core variable AB_NR remains highly significant. It can be seen that obtaining excess returns through AB_NR mainly relies on its own characteristics, rather than taking on high risks. Therefore, the anomaly in the A-share market does not obey the interpretation of risk compensation.

## 5.2. Are excess returns due to mispricing?

### 5.2.1. Excess returns and different arbitrage costs

Shleifer and Vishny(1997)[13] believe that when arbitrage costs exist in the market, it is difficult for arbitrageur to correct the wrong pricing, and the wrong pricing will persist. Many of the anomalies in asset pricing stem from mispricing caused by limited arbitrage. In order to verify whether the anomaly is due to pricing errors caused by limited arbitrage, this paper selects two indicators, heterogeneous volatility (IVOL) and illiquidity (Illiq), to measure the arbitrage cost. High characteristic volatility is considered to be an important factor hindering arbitrage activities [14]. Therefore, the greater the IVOL, the greater the arbitrage cost. Illiquidity indicator Illiq (Amihud, 2002)[15] is a reverse indicator to measure stock liquidity. The greater the value of Illiq, the greater the impact of price per unit order and the greater the arbitrage cost of arbitrageurs.

**Table 6.** Returns of portfolio under different arbitrage costs

| | | AB_NR | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | L | 2 | 3 | 4 | H | H-L | t |
| IVOL | L | 2.255 | 2.334 | 2.373 | 2.459 | 2.290 | 0.035 | 0.25 |
| | M | 1.848 | 2.040 | 2.012 | 2.096 | 2.070 | 0.222 | 1.34 |
| | H | 0.732 | 1.080 | 1.145 | 1.193 | 1.282 | 0.550*** | 3.14 |
| Illiq | L | 0.820 | 1.139 | 1.169 | 1.176 | 1.076 | 0.256 | 1.37 |
| | M | 1.339 | 1.736 | 1.769 | 1.892 | 1.803 | 0.464*** | 3.41 |
| | H | 2.411 | 2.566 | 2.751 | 2.824 | 2.847 | 0.436*** | 3.02 |

In Table 6, the High group of idiosyncratic volatility and illiquidity represents the high arbitrage cost group. In Table 6, H-L represents long 30% of stocks with the highest AB_NR value and short 30% of stocks with the lowest AB_NR value at the end of each month to construct the original excess return of the hedging strategy portfolio. It can be seen that the excess return of long-short portfolio in stocks with high arbitrage cost (0.55% and 0.44%) is significantly higher than that in stocks with low arbitrage cost (0.35% and 0.26%), and the excess return exists significantly in high arbitrage cost, but does not exist in low arbitrage cost, indicating that the excess return tends to be caused by mispricing.

### 5.2.2. Excess returns and different investor sentiment

Previous studies have shown that investor sentiment has a significant impact on financial markets [16][17]. In a market dominated by sentiment, asset prices can become detached from their underlying value, resulting in mispricing. In combination with the high proportion of individual investors in A-shares, they are more willing to participate in market transactions when market sentiment is high, thus increasing the possibility of mispricing and making the anomaly more significant. This paper takes Yi Zhigao and MAO Ning (2009) [18] as the monthly market sentiment indicator, and obtains CICSI monthly data from the CSMAR database from 2006 to 2022. Taking the median as an example, all stocks are divided into groups with high sentiment and low sentiment. Table 7 shows the abnormal performance under different investor sentiment.

**Table 7.** Returns of portfolio under different investor sentiment

| | | Raw return | t | FF3 Alpha | t |
|---|---|---|---|---|---|
| High Sentiment | Low | 0.725 | 0.64 | 0.614 | 0.56 |
| | High | 1.232 | 1.06 | 1.112 | 1.02 |
| | H-L | 0.508*** | 3.36 | 0.498*** | 3.38 |
| Low Sentiment | Low | 2.230** | 2.03 | 2.037* | 1.90 |
| | High | 2.507** | 2.42 | 2.419** | 2.32 |
| | H-L | 0.277 | 1.58 | 0.382** | 2.28 |

In Table 7, High Sentiment represents the period of high investor Sentiment, and Low Sentiment represents the period of low investor sentiment. High indicates the high AB_NR group. Low indicates the low AB_NR group, and H-L indicates the hedge combination constructed based on AB_NR. Raw return represents the original yield, and FF3 Alpha represents the yield adjusted by the three-factor model. By comparing the significance and premium of the anomaly in the period of high investor sentiment and low investor sentiment, we found that the anomaly was significant in the period of high investor sentiment, but not significant in the period of low investor sentiment, and the anomaly in the period of high investor sentiment (0.51%) was greater than the premium in the period of low investor sentiment (0.28%). In combination with 4.1 and 4.2.1, the anomaly does not follow the risk compensation interpretation, and the performance is more significant at high arbitrage cost, it can be basically judged that the anomaly is caused by mispricing rather than risk premium.

# 6. Summary and Conclusions

Inspired by the ability of the overnight return day reversal triggered by the long/short confrontation of heterogeneous investors in the US stock market to predict the future return of stocks on A cross-sectional basis, this paper explores whether the frequent overnight return day reversal in the A-share market has a similar cross-sectional prediction ability. The conclusions are as follows: (1) After controlling the characteristics of scale, book-to-market ratio, reversal effect, profitability, turnover rate, etc., the abnormal frequency of opening high and closing low in A-share market is significantly positively correlated with the future return of stocks, but the abnormal frequency of opening low and closing high has no significant and stable correlation with the future return of stocks. (2) The long-short portfolio was constructed according to AB_NR, and it was found that the long-short portfolio could obtain 0.63% monthly excess return, and the excess return could not be explained by the existing pricing model. (3) In the period of stocks with high arbitrage costs and high market sentiment, the over-performance of long-short strategy portfolios is more significant. (4) The anomaly is due to mispricing rather than risk premium.

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