# The MAX Effect in China's A-Share Market from the Perspective of Investor Behavior 

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#### Abstract

In recent years, the discovery of the MAX effect has impacted strongly the validity of factor pricing models, while investor behavior has always played a crucial role in market investment and directly influenced price formation. Based on this, using daily and monthly data of A-shares from 2005 to 2020, the paper confirms that the MAX effect still exists with the development and improvement of financial markets and can be explained by the overpayment due to investors' lottery preferences through variable grouping return analysis, portfolio return analysis based on long-short strategy construction and Fa -ma-Macbeth regression methods. The relationship between investor sentiment and the MAX effect is also analyzed by constructing an investor sentiment index, ISM, through principal component analysis, which shows that investor sentiment has an amplifying influence on the MAX effect, and high investor sentiment leads to stronger reversal of high MAX stock returns. By introducing investor attention to further study, we find that for high attention lottery stocks, investor sentiment can increase the degree of investors' conversion from attention to trading behavior, which in turn makes the MAX effect stronger.


## Keywords

Investor Sentiment, MAX Effect, Principal Component Analysis, Investor Attention, Chinese Stock Market

## 1. Introduction

Traditional financial theory suggests that capital markets are efficient. However, as research has progressed, an increasing number of phenomena have emerged that cannot be explained by the Efficient Market Hypothesis. Scholars refer to these phenomena as "anomalies", such as the MAX anomaly (MAX effect), idio-
syncratic volatility anomaly, and the mystery of low-priced stock premiums. Behavioral finance, by breaking the traditional assumption of "rational individuals", believes that investors are not always rational, and the actual trading prices of stocks can be influenced by investor behavior, such as investor sentiment and attention. This provides the possibility for a better understanding of various anomalies. Investors' attention to stocks is the starting point for a series of trading behaviors and significantly increases the likelihood of triggering trading activities, eventually leading to changes in stock prices (Zhu et al., 2016). In addition, investor sentiment can reflect speculative tendencies. During periods of high investor sentiment, investors tend to have a positive and optimistic attitude towards the stock market, which can lead to occurrences of overpayment for stocks. Therefore, studying market anomalies from the perspective of behavioral finance has practical significance.

Since Bali et al. (2011) first proposed that the maximum daily return in the current month significantly predicts negative future returns using U.S. data, i.e., the MAX effect, it has gained attention, and stocks with high MAX portfolios have been found to fit the definition of a lottery stock. As a market anomaly, the research on the MAX effect in the Chinese stock market is relatively limited, with most studies focusing on proving its existence. Moreover, few studies on the relationship between investor sentiment and the MAX effect have come to inconsistent conclusions. Additionally, existing research focuses more on the individual impact of investor sentiment or attention on the MAX effect, with rare in-depth analysis involving all three factors simultaneously.

Furthermore, due to the late development of China's stock market and its ongoing process of improvement, there have been periods of significant price fluctuations within a short period of two months in 2015, and the uncertainty and higher risk premium are closely related to the irrational behavior of investors (Chen et al., 2019a). In recent years, the China Securities Regulatory Commission has emphasized the continuous improvement of the quality of listed companies and encouraged value investment to ensure the healthy development of the stock market. Based on the above background, the research in this paper contains the following main contributions: First, we confirm that the MAX effect still exists with the development and improvement of the financial market, and the effect can be explained by the overpayment due to investor's lottery preference, which provides new empirical evidence and economic explanations for the related research on the MAX effect. Second, this paper finds that investor sentiment can not only amplify the MAX effect, but also further concludes that investor attention has an exacerbating effect, which provides a theoretical basis for investors' rational investment and market regulation suggestions.

## 2. Literature Review

### 2.1. Existence of the MAX Effect

Since Sharpe (1964) pioneered research on the Capital Asset Pricing Model
(CAPM) based on the capital market theory, asset pricing has become an indispensable part of modern financial research. However, the emergence of various anomalies in the stock market has shaken the foundations of asset pricing and market efficiency theories based on the Fama-French three-factor and CAPM models. The MAX effect is one of these hot topics. In 2011, Bali et al. (2011) first proposed the existence of the MAX effect in the US stock market using data from 1926 to 2005. They found that high-MAX portfolios are characterized by small size, low liquidity, low prices, and high heteroskedasticity, which is consistent with the definition of lottery-type stocks. As the correlation between the Chinese and US stock markets gradually increased, in 2013, Jiang and Chen (2013) used A-share data from 1997 to 2011 to demonstrate the significant MAX effect in the Chinese A-share market, which is more pronounced during bullish periods. In 2018, Cheon and Lee (2018) studied the MAX effect in 42 countries worldwide and confirmed its existence in most countries ( 25 out of 42 ), with the notable exception that their study indicated that China's stock market does not exhibit the MAX effect. In 2018, Dong et al. (2018) discovered the existence of the MAX effect in the Chinese stock market using data samples from 1997 to 2014.

### 2.2. Investigation of the Causes of the MAX Effect

An increasing number of studies indicate that investors' gambling or speculative behavior has a certain impact on stock returns (Zheng \& Sun, 2013), and the introduction of lottery-type stocks further explains this phenomenon. Lottery-type stocks, defined by Barberis and Huang (2008) as stocks with positive skewness, were found to be preferred by investors in their study. Kong et al. (2010) divided stocks into lottery-type stocks and non-lottery-type stocks based on stock characteristics and confirmed the presence of a lottery preference premium in the Chinese stock market, consistent with the conclusions of Liang and Zhang (2017) and Zhu and Zhang (2020). Bali et al. (2011) and Eraker and Ready (2015) found that lottery-type stocks align with the interests or preferences of speculators, resulting in their overpayment and lower diversification among investors, which explains the emergence of the MAX effect. Jiang and Chen (2013) explored gambling behavior in the Chinese A-share market based on Bali's research, explaining the MAX effect through the relationship between lottery-type stocks and stocks with the maximum daily returns. Cui and Wang (2016) determined the most representative indicator of lottery-type stocks based on the negative abnormal returns and positively skewed returns of multiple indicators.

### 2.3. Investigation of the Mechanisms of the MAX Effect

Regarding investor sentiment, Miller (1977), Xue and Zhang (2020) and Liu and Wen (2023) found that investors' speculative psychology is reflected in their emotions, and market short-selling restrictions lead to the manifestation of most
investors' optimistic sentiment in stock prices, resulting in overvaluation. Brunnermeier et al. (2007) found that humans are more likely to expect favorable outcomes, so investors are inherently optimistic, leading to their overestimation of a stock's future good returns. Fong and Toh (2014) discovered that the prices of high-MAX stocks are more influenced by high investor sentiment. Sun and Liu (2017) constructed an investor sentiment index (principal component analysis) to measure investor sentiment in the Chinese stock market and found that the MAX effect is more pronounced when investor sentiment is relatively high.

Regarding investor attention, Merton (1987) and Zhang et al. (2020) found that investor attention to stocks is a prerequisite for subsequent trading. Only when investors pay continuous attention to stocks and further analyze them will it translate into actual action. Barber and Odean (2008) showed that due to limited attention, investors are easily attracted to some attention-catching events (stocks), which can affect their decision-making behavior. Cheon and Lee (2018) analyzed the MAX effect globally using the US VIX index as a proxy for sentiment and found that the MAX effect is higher during periods of low sentiment. They believed that during periods of low sentiment, stocks with extreme returns attract investors' attention, thereby intensifying the MAX effect. Li and Liu (2019) used the Baidu Index to measure investor attention and analyzed its impact on the MAX effect, finding a positive relationship between the two and noting that the impact of investor attention on the MAX effect is influenced by market sentiment. Additionally, Chen (2021) studied the factors influencing the MAX effect from a price perspective and found that investor enthusiasm and willingness to chase returns are significantly affected by stock prices.

In summary, by reviewing past literature, we find that investors are not always fully rational and their behavior is influenced by their own cognition, preferences, and emotional changes. Based on speculative psychology, investors exhibit a preference for lottery-type stocks, indicating a gambling preference. Due to prospect theory, investors tend to overestimate stock prices by using probabilistic weighting methods, resulting in overpayment. Furthermore, investor sentiment reflects the strong subjectivity of investors and significantly influences their investment decisions (Min et al., 2017; He et al., 2021; Zhang \& Yuan, 2017). Therefore, investor sentiment likely has a significant impact on the MAX effect. Limited attention theory suggests that due to limited attention, investors selectively process a large amount of information presented in the market. Investors are likely to be attracted to events such as extreme returns, which can affect the MAX effect.

Based on the theoretical support mentioned above, this paper explores the MAX effect in the Chinese stock market. Specifically, it aims to determine whether the MAX effect remains significant in the Chinese stock market as it continues to develop and mature, and to explain its causes. Furthermore, it focuses on investigating how investor sentiment affects the MAX effect, and introduces the concept of investor attention based on the theory of limited atten-
tion to further research this phenomenon.

## 3. Data and Variable Selection

This paper selects daily and monthly data for all A-share stocks from June 2005 to June 2020, sourced from CSMAR database. In order to ensure the accuracy of the research, the following procedures were undertaken in data selection and application. Considering the unique characteristics of the financial industry, this paper excluded financial sectors such as securities companies and banks when selecting data. Furthermore, stocks of PT, ST, and *ST companies were excluded due to special treatment. Additionally, to mitigate the impact of extreme values on the results, data with less than 10 trading days in a month were removed, and a $1 \%$ and $99 \%$ truncation was applied to all continuous variables. The definitions of the relevant variables are shown in Table 1. Maximum daily return (MAX): Following Bali's method, this paper selects the maximum daily data of stocks from the previous month as the MAX value. That is, $\mathrm{MAX}_{i t}=\max \left(R_{i t-1}\right)$, where $R_{i t 1 d}$ represents the return of stock $i$ on the dth trading day of the previous month $t-1$, considering the individual stock daily returns including cash dividends. Idiosyncratic volatility (IVOL): This paper calculates idiosyncratic volatility (IVOL) using daily data from the previous month. Firstly, a regression is carried out using the Fama-French three-factor model to obtain the residuals. Then, the standard deviation of the regression residuals is used to calculate the idiosyncratic volatility of the stock. Other control variables: PRICE represents the monthly closing price of the previous month. SIZE refers to the size of the listed company, represented by the total market value at the end of the previous period ( $t-1$ period). B/M represents the book-to-market ratio. REV denotes the monthly return of the previous month. ZR is calculated as the ratio of ze-ro-return days to the total trading days of the month, which is a proxy variable widely used to measure illiquidity, as proposed by Lesmond (2005). $\beta_{\text {SMB }}, \beta_{\text {RMRF }}$, $\beta_{\text {HML }}$ represent the loadings of the three factors in the Fama-French three-factor model. ISKEW represents idiosyncratic skewness, which is calculated by obtaining the skewness of residuals from regressions involving individual stock daily returns, Fama-French three-factor model daily data, and daily risk-free rate. MOM represents the momentum factor, which is the cumulative return from month $t-1$ to month $t$, considering the reinvestment of cash dividends.

## 4. Empirical Process and Results Analysis

### 4.1. Analysis of Stocks with High MAX and Lottery-Type Stocks

To determine whether stocks with high MAX values are lottery-type stocks, this paper first conducts descriptive statistical analysis on the distribution of returns for portfolios of stocks with high and low MAX values in the subsequent month. The high (low) MAX portfolios are based on the top (bottom) deciles of the MAX distribution. All results in the table are presented in percentage (\%).

Table 1. Summary of variable definitions.

| Variable symbols | Variable name and calculation method |
| :---: | :---: |
| MAX | Maximum daily return, obtained based on daily data of the previous month |
| IVOL | Heterogeneous fluctuations, obtained based on daily data of the previous month |
| ISKEW | Heterogeneous skewness, obtained based on the calculation of heterogeneous fluctuations |
| SIZE | Size of listed companies, expressed as total market capitalization at the end of the previous month |
| PRICE | Monthly closing prices, obtained based on the previous month's monthly data |
| B/M | Owner's equity/Market capitalization outstanding |
| REV | Last month's earnings |
| ZR | Number of zero return days in the month divided by the total number of trading days in the month, measuring illiquidity |
| MOM | Cumulative momentum factor, total return considering cash dividends reinvested from period $t-1$ to period $t-12$ |
| $\beta_{\text {SMB }}, \beta_{\text {RMRF }}, \beta_{\text {HML }}$ | Size, market and book-to-market ratio factor loadings |

As can be seen from Table 2, for stocks with high MAX, their mean value of -0.05 is smaller and negative compared to the mean value of 1.32 for stocks with low MAX, implying that on average investors investing in portfolios of stocks with high MAX are more likely to suffer large losses in the future than those investing in portfolios of stocks with low MAX. This may be due to the fact that investors focus more on high MAX stocks causing current stock prices to overreact and price corrections to future returns. Additionally, the absolute values of all remaining indicators for the high MAX portfolios are significantly higher than those of the low MAX portfolios, and the high MAX portfolios exhibit a larger positive skewness (57.56). All these results indicate that investors who invest in portfolios with high MAX stocks will face higher investment risks, which may result in lower or even negative returns in the future. Therefore, as suggested by previous research, investing in portfolios with high MAX stocks is more similar to investing in lottery-type stocks.

Furthermore, the characteristics of stocks affected by the MAX effect may be the cause of abnormal stock returns. To address this concern, this study describes these stock characteristics. Before conducting the descriptive statistics, decile portfolios based on the MAX of each stock each month are constructed, and then the characteristics of these portfolios are analyzed. Table 3 reports the results of the descriptive statistics, where "low max" ("high max") represents the portfolios with the lowest (highest) maximum daily returns in the previous month ( $t-1$ month), gradually increasing from D 2 to D 9 . The values in the table represent the means.

Table 2. Characteristics of future returns for high and low MAX portfolios.

|  | Mean | Std. | P99 | P1 | Skew |
| :---: | :---: | :---: | :---: | :---: | :---: |
| High max | -0.05 | 13.82 | 39.01 | -28.00 | 57.56 |
| Low max | 1.32 | 10.89 | 33.44 | -25.33 | 45.27 |

Table 3. Characterization based on the MAX portfolio.

|  | MAX <br> $(\%)$ | IVOL <br> $(\%)$ | PRICE | SIZE <br> $(10$ millions) | B/M | REV (\%) | ZR (\%) | $\beta_{\text {SMB }}$ | $\beta_{\text {RMRF }}$ | $\beta_{\text {HML }}$ | ISKEW MOM (\%) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Low max | 2.52 | 10.26 | 11.29 | 715 | 0.72 | -3.57 | 52.21 | 0.39 | 0.98 | -0.29 | 2.79 | 0.73 |
| D2 | 3.25 | 10.67 | 12.01 | 611 | 0.68 | -2.48 | 52.29 | 0.46 | 1.04 | -0.33 | 2.75 | 0.73 |
| D3 | 3.77 | 10.82 | 12.86 | 595 | 0.66 | -1.85 | 52.36 | 0.46 | 1.03 | -0.47 | 2.78 | 0.72 |
| D4 | 4.30 | 11.20 | 13.55 | 588 | 0.64 | -1.11 | 52.36 | 0.44 | 1.01 | -0.53 | 2.68 | 0.75 |
| D5 | 4.83 | 11.35 | 14.48 | 589 | 0.62 | 0.00 | 52.59 | 0.40 | 1.04 | -0.66 | 2.70 | 0.69 |
| D6 | 5.40 | 11.43 | 15.18 | 604 | 0.61 | 0.92 | 52.63 | 0.43 | 1.02 | -0.61 | 2.69 | 0.74 |
| D7 | 6.22 | 11.72 | 15.99 | 615 | 0.59 | 2.50 | 52.65 | 0.41 | 1.03 | -0.68 | 2.63 | 0.70 |
| D8 | 7.21 | 11.73 | 16.89 | 623 | 0.59 | 3.77 | 52.71 | 0.35 | 1.03 | -0.69 | 2.71 | 0.75 |
| D9 | 8.80 | 11.88 | 17.36 | 595 | 0.58 | 6.17 | 52.73 | 0.31 | 1.03 | -0.71 | 2.69 | 0.74 |
| High max | 9.98 | 11.99 | 14.96 | 495 | 0.59 | 8.77 | 52.65 | 0.50 | 1.13 | -0.54 | 2.70 | 0.71 |

From Table 3, it can be seen that the highest group (high max) has an average MAX value of up to $9.98 \%$, while the lowest group (low max) has an average MAX value of only $2.52 \%$. As MAX increases, the idiosyncratic volatility (IVOL) and the monthly return from the previous month (REV) show a monotonic increase, while the loading of the book-to-market ratio factor ( $\beta_{\mathrm{HML}}$ ) shows a monotonic decrease, and they all exhibit stable changes. These results are consistent with the findings of Cheon and Lee (2018). As MAX gradually increases, the price initially increases and then decreases. This phenomenon is mainly due to the fact that the true value of stocks in the Chinese stock market is not well reflected by stock prices. The momentum factor (MOM) for portfolios with high MAX stocks is lower than that for portfolios with low MAX stocks, indicating that portfolios that have experienced losses in the past year are more likely to exhibit larger jumps in prices in the following year. In conclusion, from Table 3, it can be observed that portfolios with high MAX values have relatively lower stock prices, higher idiosyncratic volatility, higher returns in the previous month, and positive skewness. All these characteristics align with the features of lottery-type stocks, indicating that portfolios with high MAX stocks are essentially lottery-type stocks, which investors are likely to show a preference for.

### 4.2. Lottery Stock Preference and Overpayment

Due to investors' special preference for lottery stocks, they are likely to overpay for this type of stocks. If investors overpay for portfolios consisting of high MAX stocks, it will lead to a future decline in stock prices, indicating that MAX can
predict stock returns in the opposite direction. To verify this hypothesis, we first observe the Pearson correlation coefficient matrix and find that MAX is negatively correlated with the monthly stock returns ( -0.0561 ), which preliminarily suggests that the more investors favor lottery-type (high MAX) stocks, the more likely they are to overpay for this type of stocks, resulting in a reversal of future returns, indicating the presence of the MAX effect.

To further investigate whether investors overpay for high MAX stocks and whether MAX can predict future stock returns, this study conducts company-level Fama-Macbeth regressions by regressing the maximum daily returns (MAX) on the monthly returns in the following month. The two-step cross-sectional regression method effectively avoids the interference of residual correlation on standard errors.

Table 4 presents the Fama-Macbeth regression results of company-level maximum daily returns (MAX) and other control variables on stock returns. To control for the influence of other stock characteristics, all non-core variables in Table 1 are included as control variables to make the results more reliable. The table reports the coefficients and $t$-values of each variable, and considering the influence of autocorrelation, the $t$-values are calculated using Newey-West adjusted standard errors (Newey and West, 1987) with a lag of 6 months. The table also reports the goodness-of-fit $\mathrm{R}^{2}$ and adjusted $\mathrm{R}^{2}$.

From Table 4, it can be observed that the coefficients of maximum daily returns (MAX) are all negative, indicating a negative relationship between MAX and future returns, and all coefficients are significant at the $1 \%$ level. This provides strong evidence of significant reversal in the returns of stocks with high MAX. Due to the observation from Table 3 that idiosyncratic volatility (IVOL) monotonically increases with MAX, and to eliminate the suspicion that IVOL may cause return reversal, three regressions (1), (2), and (3) are performed. Regression (1) includes only MAX and other control variables but excludes IVOL. Regression (2) includes both MAX, IVOL, and other control variables. Regression (3) includes only IVOL and other control variables, excluding MAX. In regressions (1) and (2), the coefficients of MAX are all negative, and after introducing IVOL, the absolute values of the coefficients increase from 0.325 to 0.328 , and the $t$-values change from -4.79 to -4.90 , indicating a more significant negative predictive effect of maximum daily returns on future returns.

Furthermore, in regression (3) of Table 4, the coefficient of IVOL is significantly negative, indicating a negative relationship between IVOL and future returns. However, when reviewing the coefficient of IVOL in regression (2), it is observed to be a positive value of 0.0626 , and it is also significant at the $1 \%$ level. This suggests that the negative correlation of IVOL in regression (3) is due to the absence of an important control variable, namely MAX, which may mislead the readers into thinking that the return reversal is caused by IVOL, whereas it is actually influenced by MAX. Therefore, it is the existence of the MAX effect that leads to the subsequent reversal of stock returns, fully confirming that investors not only prefer stocks with high MAX but also tend to overpay for this type of
stocks, ultimately resulting in a reversal of returns in the following month.

### 4.3. Investigation of the Existence of the MAX Effect

To further examine the existence of the MAX effect in the Chinese stock market, this study constructs portfolios by buying (selling) stocks with high MAX and selling (buying) stocks with low MAX in order to analyze the presence of the MAX effect. The stocks are sorted into deciles based on their MAX values, and the portfolio characteristics for each decile are calculated. Table 5 reports the raw returns, risk-adjusted returns (alpha), and t -statistics for each portfolio. The raw returns represent the monthly returns of each portfolio. Additionally, the risk-adjusted returns (alpha) are calculated using the Fama-French three-factor model (FF3) as shown in Equation (4.1).

Table 4. Results of Fama-Macbeth regression.

| Variable | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
| MAX | $\begin{gathered} -0.325^{* * *} \\ (-4.79) \end{gathered}$ | $\begin{gathered} -0.328^{* * *} \\ (-4.90) \end{gathered}$ |  |
| IVOL |  | $\begin{gathered} 0.0626^{* * *} \\ (2.74) \end{gathered}$ | $\begin{gathered} -0.0599^{* * *} \\ (-12.40) \end{gathered}$ |
| $\beta_{\text {RMRF }}$ | $\begin{gathered} 0.0438 \\ (1.37) \end{gathered}$ | $\begin{gathered} 0.0448 \\ (1.43) \end{gathered}$ | $\begin{gathered} 0.0744^{*} \\ (1.91) \end{gathered}$ |
| $\beta_{\text {SMB }}$ | $\begin{gathered} 0.0088 \\ (0.62) \end{gathered}$ | $\begin{gathered} 0.0076 \\ (0.55) \end{gathered}$ | $\begin{gathered} -0.0258^{* *} \\ (-2.34) \end{gathered}$ |
| $\beta_{\text {HML }}$ | $\begin{gathered} -0.0193^{* *} \\ (-2.16) \end{gathered}$ | $\begin{gathered} -0.0178^{\star *} \\ (-2.08) \end{gathered}$ | $\begin{gathered} 0.0132^{* * *} \\ (3.00) \end{gathered}$ |
| Ln(size) | $\begin{aligned} & -0.0048 \\ & (-1.62) \end{aligned}$ | $\begin{aligned} & -0.0044 \\ & (-1.57) \end{aligned}$ | $\begin{gathered} -0.0020^{* * *} \\ (-4.48) \end{gathered}$ |
| $\operatorname{Ln}(\mathrm{B} / \mathrm{M})$ | $\begin{gathered} -0.0300^{* * *} \\ (-7.36) \end{gathered}$ | $\begin{gathered} -0.0297^{* * *} \\ (-7.22) \end{gathered}$ | $\begin{gathered} -0.0541^{* * *} \\ (-50.40) \end{gathered}$ |
| Ln(MOM) | $\begin{gathered} 0.0069 \\ (0.32) \end{gathered}$ | $\begin{gathered} 0.0088 \\ (0.40) \end{gathered}$ | $\begin{gathered} -0.0195^{* * *} \\ (-39.47) \end{gathered}$ |
| ZR | $\begin{gathered} 0.0352^{* * *} \\ (5.10) \end{gathered}$ | $\begin{gathered} 0.0346^{* * *} \\ (5.00) \end{gathered}$ | $\begin{gathered} -0.0898^{* * *} \\ (-29.82) \end{gathered}$ |
| ISKEW | $\begin{gathered} 0.0037 \\ (0.24) \end{gathered}$ | $\begin{gathered} 0.0035 \\ (0.23) \end{gathered}$ | $\begin{gathered} 0.0048 \\ (1.17) \end{gathered}$ |
| Ln (PRICE) | $\begin{aligned} & 0.0015 \\ & (0.36) \end{aligned}$ | $\begin{gathered} 0.0009 \\ (0.22) \end{gathered}$ | $\begin{gathered} -0.0146^{* * *} \\ (-19.55) \end{gathered}$ |
| REV | $\begin{gathered} -0.0298 \\ (-1.48) \end{gathered}$ | $\begin{aligned} & -0.0299 \\ & (-1.52) \end{aligned}$ | $\begin{gathered} -0.0459^{* * *} \\ (-11.09) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.101 | 0.104 | 0.080 |
| Adj. $\mathrm{R}^{2}$ | 0.095 | 0.098 | 0.080 |
| N | 63,878 | 63,878 | 66,896 |

${ }^{*},^{* *}$ and ${ }^{* * *}$ denote significance is statistically significant at the $10 \%, 5 \%$ and $1 \%$ levels, respectively, and $t$-values are in parentheses, as below.

Table 5. Summary of the portfolio's returns.

| Panel A: Regression results of different weighted portfolios |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Equal-weighted portfolio |  |  | Outstanding market capitalization weighted portfolio |  |  | Total market capitalization weighted portfolio |  |  |
|  | Raw return | FF3 a |  | Raw return | FF3 a |  | Raw return | FF3 a |  |
|  |  | $\alpha$ (\%) | $t$ |  | $\alpha$ (\%) | $t$ |  | $\alpha$ (\%) | $t$ |
| Low max | 1.32 | $0.19^{* * *}$ | 4.26 | 1.32 | 0.18 | 4.03 | 1.32 | $0.33^{* * *}$ | 7.44 |
| D2 | 1.73 | 0.51 *** | 11.04 | 1.74 | 0.50 *** | 10.59 | 1.74 | 0.63 *** | 13.41 |
| D3 | 1.82 | $0.57^{* * *}$ | 11.81 | 1.82 | $0.57^{* * *}$ | 11.5 | 1.82 | $0.70^{* * *}$ | 14.21 |
| D4 | 1.73 | $0.54^{* * *}$ | 10.52 | 1.73 | $0.53 * * *$ | 10.18 | 1.73 | $0.66{ }^{* * *}$ | 12.87 |
| D5 | 1.72 | $0.46^{* * *}$ | 8.68 | 1.72 | $0.45{ }^{* * *}$ | 8.31 | 1.72 | $0.58{ }^{* * *}$ | 10.87 |
| D6 | 1.72 | $0.34 * * *$ | 6.28 | 1.72 | $0.33^{* * *}$ | 5.93 | 1.72 | $0.46{ }^{* * *}$ | 8.34 |
| D7 | 1.41 | 0.07 | 1.26 | 1.41 | 0.07 | 1.29 | 1.41 | $0.18{ }^{* * *}$ | 3.2 |
| D8 | 1.16 | -0.01 | -0.20 | 1.16 | $-0.03$ | -0.49 | 1.16 | $0.11^{* *}$ | 1.86 |
| D9 | 0.78 | $-0.55{ }^{* * *}$ | -9.14 | 0.78 | $-0.57 * * *$ | $-9.34$ | 0.78 | $-0.43^{* * *}$ | -6.97 |
| High max | -0.05 | $-1.35{ }^{* * *}$ | -21.38 | -0.05 | $-1.35^{* * *}$ | -21.2 | -0.05 | $-1.19^{* * *}$ | -18.76 |

Panel B: Long-short portfolio return regression results

| $\mathrm{H}-\mathrm{L}$ | -1.37 | -1.54 | -3.52 | -1.37 | -1.53 | -3.48 | -1.37 | $-1.52^{* * *}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

$$
\begin{equation*}
R_{t}^{a d j}=R_{t}+\beta_{m} \mathrm{RMRF}_{t}+\beta_{s} \mathrm{SMB}_{t}+\beta_{h} \mathrm{HML}_{t} \tag{4.1}
\end{equation*}
$$

where RMRF represents the excess return of the value-weighted market portfolio of A-shares over the 30-day interbank offered rate, SMB is the size factor, and HML is the book-to-market ratio factor. $\beta_{m}, \beta_{s}$, and $\beta_{h}$ are the factor loadings. To account for the impact of illiquidity, the results are reported for both equally weighted and market-cap (free-float market cap and total market cap) weighted portfolios.

From Panel A of Table 5, it can be observed that regardless of the weighting scheme used to construct the portfolios, the raw returns and risk-adjusted returns (alpha) are significant. Moreover, as the MAX values increase, the alpha initially increases and then decreases, eventually becoming negative. Furthermore, the portfolios with high MAX exhibit significantly lower raw returns and alphas compared to the portfolios with low MAX. Panel B of Table 5 shows that when constructing long-short strategy portfolios based on high and low MAX, the portfolio returns are significantly negative, with a raw return difference of $-1.37 \%$ and an alpha of $-1.54 \%$. This indicates that investors will experience significant negative average excess returns in the future when buying such portfolios, implying future losses for investors. Therefore, it can be concluded that the MAX effect remains significant in the Chinese stock market.

### 4.4. Construction of Investor Sentiment Index

After confirming the existence of the MAX effect in the Chinese stock market, this study investigates the impact of investor sentiment on the MAX effect. It aims to examine the relationship between the two by constructing a measurement indicator for investor sentiment. Additionally, the study explores the role of investor attention based on the focus on high and low portfolios.

Due to the limitations of single indicators in measuring sentiment adequately, composite indicators have been commonly used by scholars, often utilizing principal component analysis. In this study, a composite indicator for investor sentiment will be constructed using the principal component analysis method. Drawing inspiration from previous works by Baker and Wurgle (2006), Han and Li (2017), Xu and Zhou (2018), and Chen et al. (2019b), four indicators, namely, turnover rate (TO), price-earnings ratio (PE), consumer confidence index (CCI), and new account opening numbers (NIA), are selected to construct the investor sentiment indicator. Furthermore, to control for the common influence of macroeconomic factors on these indicators, four macroeconomic indicators related to economic prosperity, production, consumption, and finance are chosen: macroeconomic composite index (MCI), industrial production growth rate (IPI), consumer price index (CPI), and money supply (M2). The data for consumer confidence index, macroeconomic composite index, industrial production growth rate, and money supply are obtained from CSMAR, while data for the remaining indicators are sourced from RESSET database. The data selected covers the period from June 2005 to June 2020. As the data for new account opening numbers has not been published since 2015 and has been replaced by new investor numbers, which mainly refers to the number of newly effective stock accounts, the two are similar. Following the approach of Ma et al. (2020), both variables are used in combination to construct the sentiment index, denoted as ISM:

$$
\begin{align*}
\mathrm{ISM}= & 0.2542 \times \mathrm{RNIA}+0.2048 \times \mathrm{RPE}+0.2847 \times \mathrm{RCCI}+0.2642 \times \mathrm{RTO} \\
& +0.2467 \times \mathrm{LNIA}+0.2095 \times \mathrm{LPE}+0.2912 \times \mathrm{LCCI}+0.2655 \times \mathrm{LTO} \tag{4.2}
\end{align*}
$$

where R- represents the various indicators after removing the impact of macroeconomic factors, and L represents the lagged terms of the indicators. As evident from Equation (4.2), after controlling for macroeconomic effects, investor sentiment exhibits a positive correlation with all the original indicators. This implies that an increase in new account opening numbers, rising price-earnings ratios, enhanced consumer confidence index, and frequent market trading all indicate an increase in investor sentiment. Furthermore, the lagged terms of these variables are also positively correlated with investor sentiment, indicating that they serve as leading indicators for investor sentiment. Moreover, the larger these variables, the higher the investors' sentiment, and vice versa.

Furthermore, this study verifies the effectiveness of the index, namely, its ability to accurately reflect investor sentiment in the market. Firstly, the correlation
between the Investor Sentiment Index (ISM) and the Shenzhen Composite Index and Shanghai Composite Index is analyzed through regression analysis, with both market composite indices standardized. The ISM exhibits a correlation of 1.02 ( $t$-value of 13.64) with the Shanghai Composite Index and a correlation of 0.54 ( $t$-value of 5.50 ) with the Shenzhen Composite Index. This indicates a positive correlation between investor sentiment and both the Shenzhen and Shanghai Composite Indices, significantly at the $1 \%$ level. This preliminary analysis suggests that the ISM can directly reflect investor sentiment and has a significant impact on changes in the overall market conditions in China.

The variations over time of the Investor Sentiment Index (ISM), Shanghai Composite Index, and Shenzhen Composite Index are compared and analyzed using scatter plots in this study. Figure 1 reports the results, with each indicator represented by a different colored line. It can be observed from Figure 1 that the Investor Sentiment Index shows a consistent trend with both the Shanghai and Shenzhen indices. The index can effectively capture the trends and fluctuations of the two indices and accurately reflect the transition between bull and bear markets in the stock market, aligning with real-world conditions. Additionally, the growth and decline of investor sentiment consistently precede the changes in the two indices and exhibit larger magnitudes of variation. This further supports the notion that investor sentiment primarily reflects the sentiment of Chinese stock market participants and can indicate the direction of the stock market. These findings indicate the rationality and effectiveness of the constructed Sentiment Index (ISM) in this study. Thus, the ISM, which is constructed within the same time period as the analysis of the MAX effect, is used to study the relationship between the two.


Figure 1. Investor sentiment and composite index.

### 4.5. Analysis of the Impact of Investor Sentiment Index (ISM) on the MAX Effect

Based on the constructed Investor Sentiment Index (ISM), this section analyzes its impact on the MAX effect in the Chinese stock market. The analysis primarily employs two-variable grouping analysis and cross-sectional regression analysis.

This study employs a combination of variable grouping analysis to examine the relationship between investor sentiment and the MAX effect. Based on the analysis in the previous section, it is evident that investor sentiment has predictive power for future stock market trends. Therefore, this study considers investor sentiment to have a lagging effect. In the analysis of the relationship between investor sentiment and the MAX effect, the study incorporates lagged terms of the Investor Sentiment Index (ISM) for further investigation. Firstly, the study divides the MAX effect into five equal groups and further categorizes each MAX group into five subgroups based on lagged terms of the ISM. This process culminates in a $5 \times 5$ matrix that reports the monthly investment returns for each subgroup. The rows (columns) 1-5 represent the five combinations based on MAX (ISM), ranging from the lowest to the highest. Additionally, Table 6 reports the monthly returns, adjusted by the Fama-French three-factor model, for the highest and lowest MAX groups, controlling for investor sentiment. The analysis is conducted using a market capitalization-weighted approach for robust results. In this context, Hism (IISM) indicates the highest (lowest) subgroup of investor sentiment, followed by the MAX grouping from 1 to 5 , and so on. Table 6 presents the monthly combined returns based on the MAX and ISM subgroups, with all results reported in percentages.

According to Table 6, when controlling for the influence of investor sentiment, as the MAX increases, the future returns of the first to fourth columns initially increase and then decrease. Furthermore, the highest MAX group exhibits significantly lower returns compared to the lowest MAX group. When investor sentiment is at its highest (High ism), as the MAX increases, the stock returns consistently decline. Starting from D3 to the highest MAX group, the monthly stock returns are all negative. This suggests a negative predictive effect of the MAX on stock returns, which is consistent with previous research, confirming the existence of the MAX effect in the Chinese stock market.

In the results based solely on the MAX groupings, the combination with a high MAX generates a monthly return of -0.05 (Table 2). However, in the High-high combination, the monthly return is -1.48 , indicating a stronger manifestation of the MAX effect. When controlling for the MAX effect, as investor sentiment (ISM) increases, the returns of each row exhibit an increasing trend followed by a decreasing trend. As the MAX slightly increases, the stock returns in the high investor sentiment subgroup turn negative, and the magnitude of the negative returns also increases with the MAX (ranging from 0.12 to -1.48 ). These preliminary findings suggest that the presence of the MAX effect may enhance the impact of investor sentiment on future stock returns. From a long-short

Table 6. Monthly portfolio returns based on MAX and investor sentiment ISM.

|  | Low Ism | D2 | D3 | D4 | High Ism | H-L | FF3 $\alpha(\mathrm{hISM}) \mathrm{FF} 3 \alpha(\mathrm{lISM}) \mathrm{FF} 3 \alpha(\mathrm{H}-\mathrm{L})$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Low max | 1.61 | 2.27 | 2.63 | 1.31 | 0.45 | -1.16 | $0.45^{* * *}$ | $0.52^{* * *}$ | $-0.07^{* * *}$ |
| D2 | 1.86 | 2.52 | 3.04 | 1.80 | 0.19 | -1.67 | $0.36^{* * *}$ | $0.63^{* * *}$ | $-0.27^{* * *}$ |
| D3 | 1.83 | 2.72 | 3.08 | 1.67 | -0.12 | -1.95 | 0.13 | $0.51^{* * *}$ | -0.38 |
| D4 | 1.25 | 1.96 | 2.74 | 1.62 | -0.86 | -2.11 | $-0.86^{* * *}$ | 0.00 | -0.86 |
| High max | 0.36 | 0.94 | 1.99 | 0.62 | -1.48 | -1.84 | $-1.70^{* * *}$ | $-0.95^{* * *}$ | $-0.74^{* * *}$ |
| H-L | -1.25 | -1.33 | -0.64 | -0.69 | -1.93 |  |  |  |  |
| FF3 a (lMAX) | $0.52^{* * *}$ | $0.19^{* *}$ | 0.04 | $0.38^{* * *}$ | $0.45^{* * *}$ |  |  |  |  |
| FF3 a (hMAX) | $-0.95^{* * *}$ | $-1.06^{* * *}$ | $-0.74^{* * *}$ | $-0.58^{* * *}$ | $-1.70^{* * *}$ |  |  |  |  |
| FF3 a (H-L) | $-1.44^{* * *}$ | $-0.87^{* *}$ | -0.78 | $-0.96^{* * *}$ | $-2.15^{* * *}$ |  |  |  |  |

strategy perspective based on high and low combinations, whether based on maximum daily returns or investor sentiment, the H-L premium is negative for all combinations, and when both are high, the negative premium is larger.

By observing the risk-adjusted returns using the Fama-French 3-factor model, consistent conclusions are drawn. In the case of a high MAX, the risk-adjusted return for periods of high investor sentiment is $-1.70 \%$, significantly lower than the $-0.95 \%$ during periods of low investor sentiment. Furthermore, the risk premium of $-2.15 \%$ is smaller than $-1.44 \%$, and all results are significant at the $1 \%$ level. This indicates that investor sentiment strengthens the MAX effect.

To enhance the persuasiveness of the results, this study will conduct crosssectional regression analyses of investor sentiment, the MAX effect, and stock returns. Additionally, the study will divide the investor sentiment index, ISM, into high and low sentiment subgroups based on its median value. The samples above the median value will be defined as the high investor sentiment subgroup, while those below the median value will be defined as the low investor sentiment subgroup. To this end, a dummy variable, ISM1, will be introduced, with a value of 1 representing the high investor sentiment subgroup and a value of 0 indicating the low investor sentiment subgroup.

The study will employ regression models to analyze the lagged terms of the investor sentiment index (LSIM), the MAX effect, and monthly stock returns. The control variables will remain consistent with those used in the previous analysis to verify the existence of the MAX effect.

$$
\begin{align*}
R_{i t}= & \alpha_{0}+\beta_{1} \mathrm{MAX}+\beta_{2} \mathrm{LISM}+\beta_{3} \mathrm{MAX} \times \mathrm{LISM}  \tag{4.3}\\
& +\beta_{4} \mathrm{IVOL}+\beta_{5} \mathrm{ISKEW}+\beta_{6} \text { Control }+\varepsilon_{i t}
\end{align*}
$$

where $R_{i t}$ represents the monthly stock return, and MAX, LISM, IVOL, and ISKEW represent the maximum daily return, investor sentiment, idiosyncratic volatility, and idiosyncratic skewness, respectively. Control variables are the variables mentioned earlier. Table 7 presents the coefficient results of the regression analysis for each variable, with the values in parentheses indicating the corresponding t-values.

Table 7. Cross-sectional regression results based on investor sentiment.

| Variable | (1) | (2) | (3) | (4) | (5) |
| :---: | :---: | :---: | :---: | :---: | :---: |
| MAX |  | $\begin{gathered} -0.3200^{* * *} \\ (-13.15) \end{gathered}$ | $\begin{gathered} -0.2940^{* * *} \\ (-12.01) \end{gathered}$ | $\begin{gathered} -0.7360^{* * *} \\ (-11.35) \end{gathered}$ | $\begin{gathered} -0.4580^{* * *} \\ (-12.72) \end{gathered}$ |
| LISM | $\begin{gathered} -0.0027^{* * *} \\ (-5.30) \end{gathered}$ | $\begin{gathered} 0.0112^{* * *} \\ (10.04) \end{gathered}$ | $\begin{gathered} 0.0113^{* * *} \\ (10.09) \end{gathered}$ | $\begin{gathered} 0.0129^{* * *} \\ (5.17) \end{gathered}$ | $\begin{gathered} 0.0029^{* *} \\ (2.31) \end{gathered}$ |
| MAX ${ }^{\star}$ LISM |  | $\begin{gathered} -0.2240^{* * *} \\ (-13.37) \end{gathered}$ | $\begin{gathered} -0.2070^{* * *} \\ (-12.26) \end{gathered}$ | $\begin{gathered} -0.2610^{* * *} \\ (-8.10) \end{gathered}$ | $\begin{gathered} -0.4640^{* * *} \\ (-21.85) \end{gathered}$ |
| IVOL | $\begin{gathered} -0.0529^{* * *} \\ (-10.55) \end{gathered}$ |  | $\begin{gathered} -0.0414^{* * *} \\ (-8.08) \end{gathered}$ | $\begin{gathered} -0.0839^{* * *} \\ (-10.38) \end{gathered}$ | $\begin{gathered} -0.2350^{* * *} \\ (-32.53) \end{gathered}$ |
| ISKEW | $\begin{aligned} & 0.0058 \\ & (1.40) \end{aligned}$ |  | $\begin{aligned} & -0.0107 \\ & (-0.59) \end{aligned}$ | $\begin{aligned} & -0.0082 \\ & (-0.31) \end{aligned}$ | $\begin{gathered} -0.0424^{* * *} \\ (-3.98) \end{gathered}$ |
| $\beta_{\text {RMRF }}$ | $\begin{gathered} 0.0732^{*} \\ (1.87) \end{gathered}$ | $\begin{gathered} 0.0778^{*} \\ (1.90) \end{gathered}$ | $\begin{gathered} 0.0809^{* *} \\ (1.96) \end{gathered}$ | $\begin{gathered} -0.0074 \\ (-0.18) \end{gathered}$ | $\begin{gathered} -0.2060^{* * *} \\ (-5.18) \end{gathered}$ |
| $\beta_{\text {SMB }}$ | $\begin{gathered} -0.0245^{* *} \\ (-2.22) \end{gathered}$ | $\begin{gathered} -0.0143 \\ (-1.27) \end{gathered}$ | $\begin{gathered} -0.0188 \\ (-1.51) \end{gathered}$ | $\begin{gathered} 0.0809^{*} \\ (1.84) \end{gathered}$ | $\begin{aligned} & 0.0128 \\ & (1.01) \end{aligned}$ |
| $\beta_{\text {HML }}$ | $\begin{gathered} 0.0128^{* * * *} \\ (2.90) \end{gathered}$ | $\begin{gathered} -0.0106^{*} \\ (-1.93) \end{gathered}$ | $\begin{aligned} & -0.0061 \\ & (-0.78) \end{aligned}$ | $\begin{gathered} -0.0457^{* *} \\ (-2.17) \end{gathered}$ | $\begin{gathered} -0.0252^{* * *} \\ (-3.28) \end{gathered}$ |
| Ln(size) | $\begin{gathered} -0.0017^{* * *} \\ (-3.65) \end{gathered}$ | $\begin{gathered} -0.0009^{*} \\ (-1.91) \end{gathered}$ | $\begin{gathered} -0.0018^{* * *} \\ (-3.73) \end{gathered}$ | $\begin{gathered} 0.0060^{* * *} \\ (5.04) \end{gathered}$ | $\begin{gathered} 0.0021^{* * *} \\ (4.33) \end{gathered}$ |
| $\operatorname{Ln}(\mathrm{B} / \mathrm{M})$ | $\begin{gathered} -0.0543^{* * *} \\ (-50.55) \end{gathered}$ | $\begin{gathered} -0.0534^{* * *} \\ (-48.74) \end{gathered}$ | $\begin{gathered} -0.0537^{* * *} \\ (-49.02) \end{gathered}$ | $\begin{gathered} -0.0708^{* * *} \\ (-24.77) \end{gathered}$ | $\begin{gathered} -0.0435^{* * *} \\ (-39.41) \end{gathered}$ |
| Ln(PRICE) | $\begin{gathered} -0.0142^{* * *} \\ (-18.93) \end{gathered}$ | $\begin{gathered} -0.0142^{* * *} \\ (-18.39) \end{gathered}$ | $\begin{gathered} -0.0143^{* * *} \\ (-18.56) \end{gathered}$ | $\begin{gathered} 0.0071^{* * *} \\ (3.30) \end{gathered}$ | $\begin{gathered} -0.00399^{* * *} \\ (-5.00) \end{gathered}$ |
| Ln(MOM) | $\begin{gathered} -0.0205^{* * *} \\ (-38.80) \end{gathered}$ | $\begin{gathered} -0.0200^{* * *} \\ (-36.88) \end{gathered}$ | $\begin{gathered} -0.01999^{* * *} \\ (-36.79) \end{gathered}$ | $\begin{gathered} 0.0239^{* * *} \\ (12.36) \end{gathered}$ | $\begin{gathered} -0.0309^{* * *} \\ (-52.35) \end{gathered}$ |
| ZR | $\begin{gathered} -0.0899 * * * \\ (-29.85) \end{gathered}$ | $\begin{gathered} -0.0880^{* * *} \\ (-28.24) \end{gathered}$ | $\begin{gathered} -0.0888^{* * *} \\ (-28.51) \end{gathered}$ | $\begin{gathered} -0.0129^{* *} \\ (-2.03) \end{gathered}$ | $\begin{gathered} -0.1020^{* * *} \\ (-30.75) \end{gathered}$ |
| REV | $\begin{gathered} -0.04999^{* * *} \\ (-11.87) \end{gathered}$ | $\begin{gathered} -0.0277^{* * *} \\ (-6.03) \end{gathered}$ | $\begin{gathered} -0.0290^{* * *} \\ (-6.32) \end{gathered}$ | $\begin{gathered} 0.0875^{* * *} \\ (6.71) \end{gathered}$ | $\begin{gathered} -0.1730^{* * *} \\ (-34.55) \end{gathered}$ |
| $\mathrm{R}^{2}$ | 0.079 | 0.082 | 0.083 | 0.139 | 0.141 |
| N | 66,896 | 63,878 | 63,878 | 10,943 | 49,665 |

Firstly, regression (1) only includes the investor sentiment indicator and control variables. It can be observed that the coefficient of LISM is significantly negative ( -0.0027 ), indicating that investor sentiment can negatively predict future stock returns. That is, when investor sentiment is high, they tend to overly optimistic about the stock trend, ultimately leading to a reversal in stock returns. Secondly, in regression (2), MAX and the interaction term MAX $\times$ LISM are added. It is found that the coefficient of the investor sentiment indicator LISM changes from being significantly negative in regression (1) to significantly posi-
tive. Specifically, it changes from a significant negative value of -0.0027 to a significant positive value of 0.0112 . This suggests that before including MAX, the lack of control for the latent variable MAX resulted in negative prediction of stock returns by investor sentiment. However, after adding the control variable MAX, MAX plays a role in predicting future stock returns, thereby eliminating the negative predictive power of investor sentiment on stock returns. This indicates that this negative prediction is essentially caused by the variable MAX, which is due to the overpricing of stocks with extreme returns by investors. Additionally, the coefficients of MAX and the interaction term MAX $\times$ LISM are both negative and significant at the $1 \%$ level. This further confirms the presence of the MAX effect in China's stock market, and investor sentiment significantly amplifies the MAX effect. When investor sentiment is high, if individual stocks exhibit extreme returns, a greater number of speculative investors who favor lottery-type stocks will translate their attention to stocks with extreme returns into impulsive buying behavior. This leads to a stronger overvaluation of short-term stock prices and subsequently larger reversals in returns. Moreover, this paper adds heteroscedasticity and heteroskedastic skewness on the basis of regression (2) to avoid this result being another form of heteroskedasticity and heteroskedastic volatility anomaly. Regression (3) shows consistent conclusions with the previous analysis, and the results are more robust.

To avoid the influence of overall market trends on the results, this study divides the samples into bull market periods and bear market periods to investigate the impact of investor sentiment on the MAX effect. The study categorizes the stock market into three bull market periods and three bear market periods based on the Shanghai-Shenzhen 300 Index rising or falling by more than $50 \%$. The bull market periods are 2005.8-2007.10, 2008.11-2009.8, and 2014.4-2015.6, while the bear market periods are 2007.11-2008.10, 2009.9-2014.3, and 2015.7-2020.6. The paper combines the three bull (bear) market periods into one combined bull (bear) market sample and conducts cross-sectional regression analysis based on these samples. Regression results and t -values are reported in Table 7, with (4) representing the bull market sample and (5) representing the bear market sample.

From the results in Table 7, it can be observed that, regardless of whether it is a bull market period or a bear market period, the coefficients of MAX and the interaction term between MAX and investor sentiment are negative, while the coefficient of investor sentiment LISM is positive, and all of them are significant at the $1 \%$ level. This indicates that the impact of investor sentiment on the MAX effect is not influenced by the overall rise or fall of the stock market; investor sentiment consistently exerts a robust and significant promotion effect on the MAX effect. When investor sentiment is high, they have a positive outlook on the stock market and, combined with their preference for lottery-type stocks, they tend to overpay for stocks with high MAX, leading to stronger reversal in future returns. Comparing the bull and bear market periods, it is found that the
coefficient of MAX in the bull market ( -0.7360 ) is significantly smaller than that in the bear market $(-0.4580)$, with a difference of 0.2780 . This indicates that this phenomenon is more pronounced during the rising period of the stock market. When the overall market trend is good and investor sentiment is high, irrational and speculative investors become more optimistic, leading to a greater possibility of impulsive "consumption" by investors, which ultimately results in a strong reversal in returns for stocks with extreme returns.

Furthermore, this paper divides the investor sentiment into high and low sentiment groups and conducts grouped regression analysis of future returns with various variables using the Fama-Macbeth regression method. The results are presented in Table 8, where ISM1 $=1$ represents the high sentiment condition and ISM1 $=0$ represents the low sentiment condition. The values in parentheses indicate the adjusted t -values.

Table 8. Analysis of regressions based on investor sentiment portfolio.

| Variable | $\mathrm{ISM}_{1}=1$ | $\mathrm{ISM}_{1}=0$ | $\mathrm{ISM}_{1}=1$ | $\mathrm{ISM}_{1}=0$ |
| :---: | :---: | :---: | :---: | :---: |
| MAX | $-0.3490^{* * *}$ | $-0.3090^{* * *}$ | $-0.3530^{* * *}$ | $-0.3060^{* * *}$ |
|  | $(-2.97)$ | $(-3.84)$ | $(-2.97)$ | $(-4.19)$ |
| IVOL |  |  | -0.0007 | $0.1190^{* * *}$ |
|  |  |  | $(-0.04)$ | $(3.33)$ |
| ISKEW |  |  | -0.0184 | 0.0229 |
|  |  |  | $(-0.98)$ | $(0.98)$ |
| $\beta_{\text {RMRF }}$ | 0.0708 | 0.0221 | 0.0800 | 0.0135 |
|  | $(1.33)$ | $(0.54)$ | $(1.57)$ | $(0.35)$ |
| $\beta_{\text {SMB }}$ | 0.0031 | 0.0126 | -0.0023 | 0.0164 |
|  | $(0.13)$ | $(0.76)$ | $(-0.10)$ | $(0.95)$ |
| $\beta_{\text {HML }}$ | $-0.0272^{* *}$ | -0.0103 | $-0.0219^{*}$ | -0.0142 |
|  | $(-2.23)$ | $(-0.94)$ | $(-2.00)$ | $(-1.08)$ |
| Ln (size) | 0.0009 | $-0.0099^{*}$ | 0.0009 | $-0.0091^{*}$ |
|  | $(0.34)$ | $(-2.08)$ | $(0.31)$ | $(-2.02)$ |
| Ln (B/M) | $-0.0326^{* * *}$ | $-0.0275^{* * *}$ | $-0.0328^{* * *}$ | $-0.0269^{* * *}$ |
|  | $(-5.85)$ | $(-4.61)$ | $(-5.84)$ | $(-4.47)$ |
| Ln (PRICE) | -0.0041 | 0.0065 | -0.0040 | 0.0053 |
|  | $(-0.64)$ | $(1.14)$ | $(-0.64)$ | $(1.00)$ |
| Ln (MOM) | 0.0251 | -0.0187 | 0.0106 | 0.0073 |
|  | $(1.66)$ | $(-0.74)$ | $(0.43)$ | $(0.20)$ |
| ZR | $0.0412^{* * *}$ | $0.0298^{* * *}$ | $0.0410^{* * *}$ | $0.0289^{* * *}$ |
|  | $(3.52)$ | $(3.79)$ | $(3.48)$ | $(3.66)$ |
| REV | -0.0260 | -0.0333 | -0.0262 | -0.0332 |
| R | $(-1.01)$ | $(-1.07)$ | $(-1.03)$ | $(-1.09)$ |
| N | 0.077 | 0.121 | 0.078 | 0.127 |
|  | 30,469 | 33,409 | 30,469 | 33,409 |
|  |  |  |  |  |

Based on the analysis of the results in Table 8, it can be observed that extreme returns of stocks have a negative predictive effect on future returns, regardless of whether investor sentiment is high or low, and these effects are significant at the $1 \%$ level. This indicates that investor sentiment is not the direct cause of stock return reversals; rather, MAX is the fundamental reason for negative future returns of stocks, and investor sentiment cannot fully explain the MAX effect but only acts as a influencing factor.

In both regressions presented in Table 8, the coefficient of MAX is significant at -0.3490 when investor sentiment is high, and -0.3090 when investor sentiment is low. This suggests that the coefficient of MAX is lower during periods of high investor sentiment compared to periods of low investor sentiment, with a difference of $4 \%$. This implies that under stable investor sentiment, more intense speculative impulses from investors during periods of high sentiment lead to lower future returns, manifested by a larger negative value of the MAX coefficient. When investor sentiment is high, it exhibits a more favorable trend towards the stock market, which results in an excessive payment for extreme returns of stocks, indicating a stronger preference for lottery-type stocks and consequently leading to larger negative returns in the future. The conclusions remain robust after controlling for heteroscedasticity and heteroskedasticity bias.

In summary, this study finds that the MAX effect following periods of high investor sentiment is greater than those following periods of low investor sentiment, which contradicts the conclusions of Cheon and Lee (2018). They argue that stocks with extreme returns attract investor attention, thereby increasing the pricing of high-MAX stocks during periods of low investor sentiment. An obvious limitation of Cheon and Lee (2018)'s study is that they did not use direct sentiment indicators or investor attention indicators but instead used proxies such as the US VIX index to analyze investor sentiment across all sampled countries. These US-based proxy variables may be ineffective for China, and global market volatility indicators may only serve as simple proxies for sentiment in the Chinese stock market. In contrast, this study's results, based on sentiment indicators constructed specifically for China, align with the findings of Fong and Toh (2014), namely, that during periods of high sentiment, investors exhibit a stronger preference for lottery-type stocks, resulting in a stronger reversal driven by excessive payments.

### 4.6. Further Research: Introduction of Investor Attention

Extreme returns of stocks (MAX) resemble salient events, attracting the attention of some irrational speculators in China's less mature stock market and promoting their trading behavior, particularly during periods of high investor sentiment. Therefore, this study will further explore the introduction of investor attention.

According to the research by Liu and Liu (2014), stocks with small market capitalization, low prices, low book-to-market ratio, increased trading volume, significant abnormal trading, and high momentum belong to stocks with high
investor attention. Hence, this study distinguishes the degree of investor attention based on stock price, market capitalization, and trading volume and conducts grouped regressions. Stocks with high investor attention refer to those with small market capitalization, low prices, and high trading volume, while stocks with low investor attention exhibit the opposite characteristics. The median values of each indicator are used as the cutoff points for grouping; values above the median are categorized as high, and values below the median are categorized as low. Thus, under the condition of controlling for high investor sentiment, this study analyzes the impact of investor attention on extreme return stocks' future returns. Table 9 reports the regression results, where ISM1 $=1$ (L) represents the impact of extreme return stocks on future returns under the combination of high investor sentiment and low investor attention, and ISM1 $=1(\mathrm{H})$ represents the combination of high investor sentiment and high investor attention. The regression controls for all the covariates mentioned earlier.

Table 9. Analysis of the regression of the portfolio of investor attention based on high investor sentiment.

| Variable | $\mathrm{ISM}_{1}=1(\mathrm{~L})$ | $\mathrm{ISM}_{1}=1(\mathrm{H})$ |
| :---: | :---: | :---: |
| MAX | 0.2260 | $-0.6690^{* * *}$ |
|  | (0.40) | (-3.55) |
| IVOL | 0.0075 | 0.0671 |
|  | (0.18) | (1.67) |
| ISKEW | 0.0584 | 0.0821 |
|  | (0.69) | (0.97) |
| $\beta_{\text {RMRF }}$ | 0.6430 | 0.0320 |
|  | (0.91) | (0.12) |
| $\beta_{\text {SMB }}$ | -0.3650 | -0.1460 ** |
|  | (-1.50) | (-2.22) |
| $\beta_{\text {HML }}$ | 0.0872 | 0.0025 |
|  | (1.18) | (0.08) |
| Ln (size) | -0.0051 | $-0.03988^{* * *}$ |
|  | (-0.52) | (-3.78) |
| Ln (B/M) | -0.0036 | $-0.0968^{* * *}$ |
|  | (-1.19) | (-3.07) |
| Ln (PRICE) | -0.0302 | $-0.0407^{* *}$ |
|  | (-1.39) | (-2.24) |
| Ln (MOM) | 0.1300 | -0.0831 |
|  | (0.94) | (-1.17) |
| ZR | 0.1340 | 0.1740 |
|  | (1.16) | (1.35) |
| REV | -0.0184 | $-0.1310^{* *}$ |
|  | (-0.20) | (-2.47) |
| $\mathrm{R}^{2}$ | 0.373 | 0.252 |
| N | 3,051 | 2966 |

According to Table 9, in portfolios where investor sentiment is high and stock attention is low, the coefficient of MAX is positive but not significant. This indicates that when controlling for investor sentiment, if investors do not pay enough attention to stocks with high MAX, there will be no subsequent series of trading behaviors. In other words, investors do not notice the occurrence of extreme returns and are less likely to overpay for such stocks, thereby affecting subsequent returns. However, since this coefficient is not significant, this paper can only make this speculation, and further research can be conducted in the future if there is an opportunity.

Observing Table 9, in portfolios characterized by high investor sentiment and high attention to extreme returns stocks, the coefficient of MAX is -0.6690 , significant at the $1 \%$ level. Moreover, this coefficient is much larger than the coefficient of high investor sentiment regression in the full sample, which is -0.3530 . This suggests that investor attention amplifies the impact of investor sentiment on MAX utility. When stocks exhibit extreme returns, they will attract an increasing number of irrational investors to pay attention to stocks with high MAX, especially those with a preference for lottery-like characteristics. If stimulated by the corresponding increase in market sentiment, the probability of turning attention into trades increases, leading to more short-term irrational trading behavior, ultimately resulting in stronger future return reversals for portfolios with high MAX. This phenomenon is consistent with logic, where investor attention is a prerequisite, and sentiment is the factor that stimulates investor trading. Investors first pay attention, then trade, and finally, the effects of their behavior are reflected in the future return reversals for stocks with high MAX.

## 5. Conclusion and Recommendations

This paper examines the MAX effect in the Chinese stock market using data from June 2005 to June 2020. By employing various methods, the existence of the MAX effect in the Chinese stock market is confirmed. Additionally, the paper constructs an Investor Sentiment Index (ISM) using principal component analysis to study the explanatory role of investor sentiment on the MAX effect. Furthermore, the paper explores the influence of investor attention on the aforementioned results, while controlling for investor sentiment. Specifically, the paper draws the following four conclusions: First, the MAX effect is still significant in the Chinese stock market and can be explained by investors' preference for lottery-like characteristics. Second, this study constructs the ISM to effectively measure investor sentiment during the period studied, which coincides with the research on the MAX effect. Third, investor sentiment alone cannot fully explain the MAX effect. It is merely one of the influencing factors. Investor sentiment promotes MAX utility, as heightened investor sentiment strengthens their gambling preference, leading to excessive payments and subsequently more pronounced return reversals. Fourth, stocks with higher investor attention exhibit
greater sensitivity to changes in investor sentiment regarding MAX utility. The paper finds that the MAX anomaly is not significant in portfolios with high sentiment and low attention, whereas in portfolios with high attention and high sentiment, the negative predictive effect of MAX on future stock returns is stronger. This indicates that extreme returns are characterized by attention-grabbing events that attract the attention of investors, which increases irrational investors' tendency to overpay, resulting in larger negative returns. This phenomenon becomes even more prominent when investor sentiment is elevated. In reality, investor attention acts as a prerequisite factor, and when investors pay attention to stocks with high MAX, the stimulation of investor sentiment intensifies their lottery-like preference, leading to a greater degree of transformation from attention to actual trading by speculative investors, thereby resulting in larger negative returns.

Based on the research content and conclusions of this paper, the following recommendations are provided: First, individual investors should enter the stock market as rationally as possible and adopt the correct speculative concept when facing stocks that exhibit extreme returns or other outstanding events. Second, institutional investors should recognize the significance of stock market sentiment and its implications. They should strive to grasp the characteristics of market trading changes caused by attention and sentiment changes, respond quickly to individual investors' excessive reactions to stocks or the market in the short term, and ensure the rapid stabilization of extreme market sentiment, thereby accelerating the transition to a normal market state. Lastly, regulatory authorities should focus on the role of social media platforms, regulate the behavior of individual investors, and prevent them from being misled by false information or spreading rumors, which may lead to adverse emotional responses and irrational investments. They should recognize the immaturity of the Chinese stock market and the irrationality of investors, and provide correct guidance to establish the proper investment concepts, thereby promoting the long-term healthy development of the stock market.

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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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