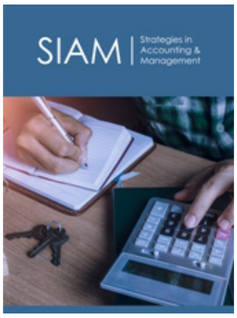
The MAX Anomaly Under Psychological Barriers: Evidence from the Chinese Stock Market

ISSN: 2770-6648



Shuai Qiao*

Dalian University of Technology, China

Abstract

This paper examines the MAX anomaly, focusing on two key issues: (1) Whether MAX stocks, as lottery-like securities, can hedge against market volatility; and (2) How the 52-week high price, serving as a psychological barrier, influences investors' gambling preferences. Our findings reveal that high-MAX stocks in the Chinese market fail to hedge market risk, suggesting that the MAX anomaly in China stems purely from gambling preferences. Furthermore, consistent with the psychological barrier hypothesis, we find that the MAX premium is negatively correlated with a stock's proximity to its 52-week high. These results indicate that investors view the 52-week high as an upper price limit, and this psychological barrier significantly impacts their preference for lottery-like stocks.

JEL classification: G10 G11.

Keywords: MAX anomaly; Market volatility; Psychological barriers; 52-week high

***Corresponding author:** Shuai Qiao, Dalian University of Technology, No.2 Linggong Road, Ganjingzi District, Dalian City, Liaoning Province, PRC, China

Submission: October 10, 2024
Published: November 14, 2024

Volume 5 - Issue 2

How to cite this article: Shuai Qiao*. The MAX Anomaly Under Psychological Barriers: Evidence from the Chinese Stock Market. Strategies Account Manag. 5(2). SIAM. 000608. 2024.
DOI: 10.31031/SIAM.2024.05.000608

Copyright@ Shuai Qiao, This article is distributed under the terms of the Creative Commons Attribution 4.0 International License, which permits unrestricted use and redistribution provided that the original author and source are credited.

Introduction

The MAX effect, characterized by the negative relationship between a stock's maximum daily return over the past month (MAX) and its future returns, has emerged as a significant anomaly in financial markets, challenging traditional asset pricing theories. This paper investigates two critical aspects of the MAX effect in the Chinese stock market: its potential role in hedging market volatility and the influence of psychological barriers, specifically the 52-week high price, on its manifestation. Our study reveals that high-MAX stocks in the Chinese market fail to provide significant hedging benefits against market risk, contrary to findings in some developed markets. This result suggests that the MAX effect in China is likely driven purely by investors' gambling preferences, rather than by any rational risk-hedging demand. Furthermore, we find a significant relationship between the MAX premium and a stock's proximity to its 52-week high price. Specifically, the MAX premium is negatively correlated with how close a stock's current price is to its 52-week high, consistent with the psychological barrier hypothesis.

These findings contribute substantially to our understanding of the MAX effect and its underlying mechanisms. The failure of high-MAX stocks to hedge market risk in China highlights the importance of market-specific factors in explaining asset pricing anomalies. It underscores the need for caution in generalizing explanations across different market contexts, particularly when considering markets with distinct institutional structures, investor bases, and regulatory environments. The interaction between the MAX effect and the 52-week high price offers intriguing insights into investor behavior and market dynamics. It suggests that investor preferences are not fixed but can vary based on a stock's price history and perceived potential for future gains. As stocks approach their 52-week highs, investors may become more cautious, tempering their appetite for lottery-like characteristics. This varying strength of the MAX effect based on price levels relative to the 52-week high emphasizes the importance of considering conditional relationships in asset pricing. Our research extends the geographical scope of MAX effect studies to one of the world's largest emerging markets, providing comprehensive evidence on its manifestation in a unique market environment. By directly testing and rejecting the hypothesis that high-MAX stocks serve as effective hedges against market volatility in the Chinese context, we challenge the generalizability of rational explanations for the MAX effect. The demonstrated novel interaction between the MAX effect and the 52-week high price provides evidence for the role of psychological barriers in shaping investor preferences for lottery-like stocks. This insight contributes to our understanding of how different behavioral biases interact in financial markets, suggesting that investor behavior is influenced by multiple, sometimes competing, psychological forces. These results have practical implications for investment strategies and risk management in the Chinese stock market. The failure of high-MAX stocks to serve as effective hedges suggests that investors seeking downside protection should look elsewhere. Moreover, the varying strength of the MAX effect based on proximity to the 52-week high offers potential avenues for more nuanced investment strategies.

Our study is grounded in the existing literature on the MAX effect, psychological barriers in finance, and asset pricing in the Chinese market. The MAX effect, first documented by Bali [1], has been observed in various markets globally, but its underlying causes remain a subject of debate. Some researchers attribute it to investors' preference for lottery-like payoffs, while others, like Barinov [2], have proposed rational explanations based on the hedging properties of high- MAX stocks. The role of psychological barriers in financial markets, particularly the 52-week high price, has been extensively studied. George [3] and Li [4] have shown that the 52-week high serves as a reference point for investors, affecting their expectations and reactions to new information. Our study bridges these two streams of literature, examining how the psychological barrier of the 52-week high interacts with the MAX effect. In the context of the Chinese market, previous studies have documented the existence of the MAX effect, but its underlying drivers and potential interactions with other market phenomena remain underexplored. Our research fills this gap, providing a comprehensive analysis of the MAX effect in this important emerging market. The remainder of this paper is organized as follows: We begin by describing our data and methodology, detailing our approach to measuring MAX, constructing portfolios, and testing our hypotheses. We then present our empirical results, including tests of the hedging hypothesis and the relationship between the MAX premium and the 52-week high. Following this, we discuss the implications of our findings, both for academic research and practical applications in investment and risk management. Finally, we conclude the paper by summarizing our key findings and suggesting avenues for future research.

Data and Variables Construction

Data

Our sample covers all stocks listed on the main boards of the Shanghai and Shenzhen A-share markets from January 2000 to December 2021. Daily and monthly individual stock trading data, company financial data, and comprehensive market trading data are sourced from the CSMAR database. Daily and monthly risk-free rates and Fama- French-Carhart [5] four-factor data are obtained from the RESSET database. The sample excludes stocks with less than 250 trading days during the sample period, observations from the first month of stock listing and those in special trading status, as well as observations with monthly returns exceeding 200% to prevent the influence of extreme values.

Variables construction

MAX and other stock characteristics: At the end of month t (portfolio construction point), $MAX_{i,t}$ is the highest return of stock i in month t [1]. To ensure the reliability of the MAX indicator, observations with less than 10 trading days in a month were excluded. In robustness tests, we also used the average of the five highest daily returns of stock i in month t as an alternative construction method for the monthly MAX indicator [6]; Zhu and Zhang, 2020.

Other stock characteristics defined at the end of month t are as follows:

$Size_{i,t}$ is the logarithm of the total market value of stock i at the end of month t-1.

$BM_{i,t}$ is the book-to-market ratio of stock i at the end of the previous calendar year for the year containing month t [7].

$MOM_{i,t}$ is the cumulative return of stock i from month t-12 to t-2 [8].

$REV_{i,t}$ is the return of stock i in month t-1 [9].

$ILLIQ_{i,t}$ is the average of the ratio of daily absolute return to daily trading volume (in yuan) of stock i in month t [10].

$BETA_{i,t}$ represents the market beta of stock i at the end of month t. It is constructed as follows to account for non-synchronous trading of stocks:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt-1} - R_{ft-1}) + \beta_{2i}(R_{mt} - R_{ft}) + \beta_{3i}(R_{mt+1} - R_{ft+1}) + \varepsilon_{it} \quad (1)$$

$$BETA_{it} = \beta_{1i} + \beta_{2i} + \beta_{3i} \quad (2)$$

$ISKEW_{i,t}$ and $COSKEW_{i,t}$ represent the idiosyncratic skewness and co-skewness, respectively, of stock i for the calendar year containing month t [1]. These two indicators are updated annually and are constructed as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \gamma_i(R_{mt} - R_{ft})^2 + \varepsilon_{it} \quad (3)$$

where $ISKEW_{i,t}$ is defined as the skewness of the residual term ϵ_{it}, and $COSKEW_{i,t}$ is the estimated coefficient $\hat{\gamma}$.

Nearness to 52-week high, NH: At the end of month t, $NH_{i,t}$ (Nearness to High) for stock i is defined as the ratio of the month-end closing price to the 52-week high price [3]. In practice, the 52-week high is taken as the highest price in the past 250 days, excluding the current day to prevent NH from always being 1 when the price equals or exceeds the high. All stock prices are adjusted for splits and dividends. When NH is not greater than 1, a larger NH means the stock price is closer to its 52-week high.

Copyright © Shuai Qiao

Market volatility factor: The paper uses the comprehensive daily returns of the Shanghai and Shenzhen A- share markets (excluding the STAR Market and ChiNext) as the market return. Following the approaches of Ang et al. [11] and Barinov [2], we construct the Chinese market volatility factor FMV. However, due to the lack of VIX trading data in the Chinese market, we use volatility fitted by the EGARCH-M model and the 21-day historical return standard deviation of the market as proxies for Market Volatility (MV). The specific construction method of FMV is as follows:

Within each month, individual stock excess returns are regressed against market excess returns and market volatility innovations (first-order difference of MV) as shown in equation (4) to obtain the sensitivity coefficient $\hat{\gamma}$ of individual stock returns to market volatility innovations:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i \Delta MV_t + \varepsilon_{it} \quad (4)$$

At the end of month t, stocks are sorted into five groups based on their sensitivity coefficients. The portfolio with the lowest coefficients is designated as MV1, and so on, with the group having the highest coefficients designated as MV5. Subsequently, across the entire sample, the market volatility innovations are regressed against the float market value-weighted excess returns of these five portfolios, as shown in equation (5):

$$\Delta MV_t = \alpha + \beta_1 (R_{MV1t} - R_{ft}) + ... + \beta_5 (R_{MV5t} - R_{ft}) + \varepsilon_t \quad (5)$$

The market volatility factor FMV is obtained by subtracting the intercept term from the fitted values of the regression.

Descriptive statistics

The mean value of the MAX indicator across the full sample is 5%, with a standard deviation of 2%. The mean value of NH is 0.74, which is consistent with its construction method. In the full sample, observations of stock prices breaking through new highs are relatively infrequent, thus NH is typically less than 1 (Table 1). At the end of month t, cross-sectional correlations between various stock indicators are calculated. Table 2 presents the time-series averages of these cross-sectional correlation coefficients. Intuitively, stocks with higher MAX are more likely to approach or even break through their 52-week highs, so the NH value should be larger. However, as shown in Table 2, the correlation coefficient between MAX and NH is only 0.09, which to some extent indicates that sorting by MAX is not homogeneous with sorting by NH. The correlation coefficient between a stock's MOM and NH reaches 0.38, which is also expected, as the former is constructed based on the stock's past performance, and higher cumulative historical returns imply that it should be closer to its high point. To rule out the possibility of high correlation when sorting by NH and MAX, we conducted the following work: At the end of month t, we divided all stocks into 5 groups based on NH and MAX respectively, then took the intersection of each pair to obtain 25 investment portfolios such as NH1-MAX1, NH1-MAX2, etc. We calculated the cross-sectional average of MAX and NH for all stocks in different portfolios. Table 3 shows the time series average of these cross-sectional means. As seen from Table 3, the distribution of the mean values of MAX (NH) does not change significantly across different NH (MAX) levels. If sorting by NH were a potential proxy for sorting by MAX, we should observe significant differences in the distribution of MAX (NH) across different NH (MAX) levels. For example, we would expect to see generally higher mean MAX values in the group of stocks with high NH. The results from Table 2 & 3 largely alleviate this concern, laying the foundation for further exploration of the interaction between MAX and NH in the following sections.

Table 1: Descriptive statistics of key variables.

	Mean	Std	Min	25%	50%	75%	Max	Count
RET	0.01	0.1	-0.37	-0.05	0	0.06	0.92	1736.86
MAX	0.05	0.02	0.01	0.04	0.05	0.07	0.18	1736.86
SIZE	15.32	0.93	13.61	14.66	15.14	15.78	20.56	1705.54
BETA	1.13	0.88	-3.96	0.65	1.11	1.59	6.36	1736.86
BM	0.67	0.2	0.1	0.54	0.68	0.82	1.23	1691.65
REV	0.01	0.1	-0.36	-0.05	0	0.06	0.91	1705.54
MOM	0.16	0.38	-0.59	-0.08	0.08	0.31	3.15	1405.41
ILLIQ	2.45	32.58	0.03	0.65	1.29	2.27	1541.64	1736.86
ISKEW	0.74	0.65	-2.95	0.38	0.72	1.08	5.53	1736.86
COSKEW	-2.17	5.96	-1.13	-5.59	-2.41	1.03	41.64	1736.86
NH	0.74	0.12	0.28	0.66	0.74	0.82	1.07	1638.31

Table 2: The correlation matrix.

Note: Coefficients in bold are significant at the 5% level.

	MAX	SIZE	BETA	BM	REV	MOM	ILLIQ	ISKEW	COSKEW	NH
MAX	1	-0.08	0.2	-0.08	0.07	0.06	-0.02	0.05	-0.01	0.09
SIZE		1	-0.06	0.14	0.07	0.23	-0.5	-0.01	0.29	0.15
BETA			1	-0.01	0	-0.02	0.01	0.01	-0.07	-0.17
BM				1	0.01	-0.13	-0.05	0.15	-0.01	0.04

Copyright © Shuai Qiao

REV					1	-0.02	-0.1	0	0.04	0.28
MOM						1	-0.15	-0.12	0.16	0.38
ILLIQ							1	0.03	-0.11	-0.09
ISKEW								1	-0.08	-0.04
COSKEW									1	0.12
NH										1

Table 3: Cross-sectional analysis of MAX and NH.

Panel A. Mean MAX (%)					
	MAX1	**MAX2**	**MAX3**	**MAX4**	**MAX5**
NH1	2.93	3.96	4.98	6.41	9.07
NH2	2.92	3.96	4.98	6.41	8.97
NH3	2.9	3.96	4.99	6.41	8.98
NH4	2.88	3.97	5	6.43	8.96
NH5	2.8	4	5.02	6.47	8.94
Panel B. Mean NH					
	NH1	**NH2**	**NH3**	**NH4**	**NH5**
MAX1	0.58	0.68	0.74	0.8	0.89
MAX2	0.57	0.68	0.74	0.8	0.89
MAX3	0.57	0.68	0.74	0.8	0.9
MAX4	0.57	0.68	0.74	0.8	0.9
MAX5	0.56	0.68	0.74	0.8	0.91

Empirical Analysis

The MAX anomaly in china

At the end of month t, stocks are sorted based on their MAX indicator and divided into 5 groups as investment portfolios. Then, a zero-cost investment portfolio is constructed by buying the group with the highest MAX and selling the group with the lowest MAX. This portfolio is held for one month until maturity. The equal-weighted and float market cap-weighted returns of the long-short portfolio (H-L) for the following month are calculated. The results are shown in Table 4. Table 4 shows that there is indeed a significant MAX anomaly in the Chinese stock market, which is consistent with existing literature using Chinese stock data as samples. Except for the average return of the float market cap-weighted long-short portfolio, which is not significant, all others are significantly negative. This means that, on average, the returns of high MAX stocks are significantly lower than those of low MAX stocks. After considering the four-factor risk, the returns of the long-short portfolio reached -1.13% (equal-weighted, t-value of -6.97) and -0.67% (float market cap- weighted, t-value of -2.66) respectively. At the same time, the negative returns of the MAX long-short portfolio are largely driven by the negative returns of high MAX stocks (i.e., the absolute value of returns for high MAX stocks is greater than that of low MAX stocks). In the float market cap-weighted group, the absolute values of both the risk-adjusted excess returns and t-values of the high MAX group are greater than those of the low MAX group. It's worth noting that the MAX anomaly is more pronounced in equal-weighted investment portfolios, suggesting that the MAX anomaly is likely a small-cap phenomenon. This is consistent with the conclusions of [6,12]. Even after controlling for multiple stock characteristics (such as SIZE, BETA, etc.) individually, the MAX anomaly remains significant, and its significance even increases. This indicates that the control variables employed are insufficient to explain the MAX anomaly cross-sectionally. Robust conclusions were also obtained from stock-level regressions based on the Fama-MacBeth approach. Due to space constraints, these results are not reported in this paper.

Table 4: Average returns and alphas of portfolios sorted by MAX.

A. Equal-Weighted				
	Average	**CAPM-alpha**	**FF3-alpha**	**FFC4-alpha**
Low MAX	1.49	0.66	0.38	0.43
	-2.34	-3.39	-2.92	-3.24
2	1.66	0.78	0.49	0.53
	-2.51	-3.83	-4.21	-4.6
3	1.49	0.6	0.34	0.35
	-2.25	-3.13	-3.01	-3.14

Copyright © Shuai Qiao

4	1.11	0.22	-0.02	-0.03
	-1.71	-1.14	(-0.19)	(-0.22)
High MAX	0.46	-0.45	-0.71	-0.71
	-0.68	(-2.05)	(-4.38)	(-4.32)
H-L	-1.03	-1.11	-1.09	-1.13
	(-6.67)	(-6.97)	(-6.98)	(-6.97)
B. Value-Weighted				
	Average	**CAPM-alpha**	**FF3-alpha**	**FFC4-alpha**
Low MAX	1.01	0.27	0.24	0.28
	-1.77	-2.02	-1.85	-2.24
2	1.07	0.23	0.19	0.22
	-1.76	-2.3	-1.81	-2.14
3	1.19	0.32	0.33	0.34
	-1.88	-3.48	-3.58	-3.73
4	0.74	-0.13	-0.1	-0.12
	-1.17	(-1.12)	(-0.88)	(-1.01)
High MAX	0.55	-0.35	-0.36	-0.39
	-0.82	(-2.05)	(-2.06)	(-2.28)
H-L	-0.45	-0.62	-0.6	-0.67
	(-1.64)	(-2.34)	(-2.30)	(-2.66)

Do the MAX stocks hedge against market volatility?

Barinov [2] introduced a market volatility risk factor (FVIX) constructed using VIX and individual stock data into the benchmark pricing model to examine whether the MAX anomaly is driven by the demand for hedging overall market volatility. After controlling for this factor, the alpha of the MAX long-short portfolio (the portfolio constructed in that paper is L-H, opposite to this paper, note the distinction) is no longer significant compared to the alpha without controlling for this factor (which was significantly positive), and the portfolio's loading on this factor is significantly negative. This implies that high MAX stocks have the effect of hedging against rising overall market volatility (hedging refers to the stock returns moving in the same direction as changes in overall market volatility), and this factor can almost completely explain the positive returns of the portfolio. Thus, it is believed that high MAX stocks have lower expected returns because they can serve as hedging tools, and investor demand for these tools leads to low returns. This section will apply the same logic to verify this in the Chinese stock market. We introduce the overall market volatility factor FMV, constructed using volatility fitted by the EGARCH-M model, into the benchmark pricing model to examine whether this factor can explain the negative returns brought by the MAX anomaly. The results are shown in Table 4, where ICAPM, FF4, and FFC5 refer to the pricing models after adding FMV to CAPM, the Fama-French three-factor model, and the Fama-French- Carhart four-factor model, respectively. β_FMV is the factor loading of FMV in the model.

It can be seen that regardless of the weighting method, after controlling for FMV, there is no significant reduction in the absolute value of alpha for the long-short portfolio (H-L) or the high MAX group, and the exposure to market volatility risk β_FMV for this portfolio is also not significant. Using other methods, such as constructing FMV using the 21-day historical return standard deviation of the market, yields similar results in testing the MAX anomaly. This is strikingly different from Barinov's [2] results based on the U.S. stock market, indicating that in the Chinese market, high MAX stocks have almost no ability to hedge against overall market volatility risk. The MAX anomaly in China seems to be entirely driven by lottery preference. This aligns with the fact that the Chinese market is dominated by retail investors who, compared to institutional investors, are often inexperienced and overconfident. Intuitively, it is unlikely that the demand for hedging against rising market volatility risk would be driven by retail investors. Based on the results of this section, we will no longer consider the possibility of the MAX anomaly being driven by the demand for hedging volatility risk in subsequent investigations.

The psychological barrier hypothesis

Based on the anchoring hypothesis of Tversky [13], research by George [3], Birru [14], and Byun et al. (2018) suggests that investors tend to view the 52-week high as an upper bound for stock prices, believing it difficult for prices to break through this level. As stock prices approach this psychological threshold, investors become hesitant. Conversely, when stock prices are far from the 52-week high, investors anchored to this reference point believe there is still significant room for price improvement, thus tending to buy such stocks. Byun et al. (2018) explored the extent to which psychological thresholds influence investors' purchases of high MAX (lottery-like) stocks, which is highly relevant to this paper's theme. This paper makes several distinctions based on their work: First, it provides an alternative explanation for the different manifestations of the MAX anomaly under psychological thresholds: Extreme positive returns occurring within a month for individual stocks may be due to (or at least provide a significant signal of) favorable news they face. Thus, high MAX values can serve as a proxy for good news about the stock, and the proximity of the stock price to its 52-week high affects investors' judgment of this news, leading to underreaction (overreaction) to the news, resulting in future positive (negative) returns. The research of Huang et al. [15] shows that investors underreact to good (bad) corporate news when stock prices are close to (far from) 52-week highs, providing empirical support for our explanation. Second, Byun et al. (2018) did not consider scenarios where stock prices break through the 52-week high. This paper makes some modifications to their hypothesis. Breaking through the 52-week high suggests the original anchor becomes ineffective, and investors adjust their expectations accordingly, anticipating further price increases Driessen et al. [16], thus boosting investor sentiment and leading to overreaction. This aligns with technical analysis perspectives: technical analysts view highs (lows) as resistance (support) lines, with breakthroughs providing buy (sell) signals [17]. Therefore, we hypothesize that when stock prices are far from highs, approaching highs, or breaking through highs, investors will overreact, underreact, and overreact to good news, respectively. Similarly, when stock prices break through 52-week lows, we expect investors to underreact to good news. Given that observations of breakouts on portfolio construction days account for a small proportion, unless otherwise specified, we will exclude these observations in our investigation to prevent different expected results from various scenarios from affecting each other.

In this section, we employ an independent double-sorting method to verify whether the MAX anomaly is related to a stock's proximity to its 52-week high. Unlike dependent double-sorting, the investment portfolios are constructed as follows: At the end of month t, all stocks are divided into 5 groups based on NH and MAX separately. Then, we take the intersection of each pair to obtain 25 investment portfolios, and finally construct long-short portfolios. Due to space constraints, we only present the results for float market cap-weighted portfolios, as shown in Table 5. The four sub-tables in Table 6 report the average returns (A) and factor-adjusted alphas (B-D) for the 25 investment portfolios, MAX long-short portfolios (rightmost column), and NH long-short portfolios (bottom row). The bottom right corner of each sub-table shows the difference in returns or alphas between the MAX long-short portfolios of the high NH group and the low NH group. As NH increases (approaching the 52-week high), the returns of high MAX portfolios (Column 5) gradually change from significantly negative to insignificant. The coefficients of NH long-short portfolios for high MAX groups are 0.79% (1.84), 0.86% (1.95), 1.14% (2.66), and 0.89% (2.36), respectively. This indicates that high MAX stocks near their 52-week highs yield higher expected returns than when they are far from their highs. This suggests that being far from the high point is more likely to cause investor overreaction, while being close to the low point leads to relative underreaction, which to some extent aligns with our expectations. However, the returns of MAX long-short portfolios do not show significant reversal as NH increases (the coefficient in the bottom right corner is positive but insignificant). The main reason for this phenomenon stems from the abnormal distribution of returns in low MAX portfolios (Column 1): as NH increases, the returns of low MAX portfolios gradually increase and become significant, which is contrary to the results observed by Byun et al. (2018). Therefore, as NH increases, even though the returns of high MAX stocks gradually change from significantly negative to insignificant, the returns of MAX long-short portfolios do not change significantly. It's worth noting that the returns of NH long-short portfolios show a "U-shaped" trend as MAX increases. In the MAX2-4 groups, the returns of NH long-short portfolios are mostly insignificant, ruling out the possibility that the results in Table 5 are entirely driven by NH [15]. In summary, investors' attitudes towards high MAX stocks are indeed influenced by their proximity to the 52-week high. In the results of equal-weighted portfolios, see Table 7, we did not observe similar results to those in Table 6. There are no significant differences in the return distributions of high MAX and low MAX stocks at different NH levels. The returns of MAX long- short portfolios are all significantly negative, while the returns of NH long-short portfolios are all insignificant. This further confirms that the MAX anomaly is concentrated in small-cap stocks, and MAX plays a dominant role in the interaction between NH and MAX [18-32].

Table 5: Do MAX stocks hedge against market volatility?

A. Equal-Weighted						
	Low MAX	2	3	4	High MAX	H-L
CAPM-alpha	0.66	0.78	0.6	0.22	-0.45	-1.11
	-3.39	-3.83	-3.13	-1.14	(-2.05)	(-6.97)
ICAPM-alpha	0.62	0.75	0.56	0.2	-0.48	-1.1
	-3.14	-3.62	-2.88	-1	(-2.14)	(-6.79)
β_FMV	-1.47	-1.43	-1.72	-0.83	-1.01	0.46
	(-1.29)	(-1.22)	(-1.41)	(-0.63)	(-0.87)	-0.72
FF3-alpha	0.38	0.49	0.34	-0.02	-0.71	-1.09
	-2.92	-4.21	-3.01	(-0.19)	(-4.38)	(-6.98)
FF4-alpha	0.37	0.48	0.32	-0.02	-0.71	-1.09
	-2.75	-4.06	-2.9	(-0.21)	(-4.43)	(-6.82)
β_FMV	-0.71	-0.62	-0.97	-0.12	-0.27	0.44
	(-1.26)	(-1.22)	(-1.81)	(-0.22)	(-0.43)	-0.64

 Copyright © Shuai Qiao

FFC4-alpha	0.43	0.53	0.35	-0.03	-0.71	-1.13
	-3.24	-4.6	-3.14	(-0.22)	(-4.32)	(-6.97)
FFC5-alpha	0.41	0.51	0.34	-0.03	-0.71	-1.12
	-3.03	-4.41	-3.04	(-0.24)	(-4.37)	(-6.80)
β_FMV	-0.83	-0.71	-1.02	-0.11	-0.28	0.55
	(-1.40)	(-1.36)	(-1.85)	(-0.20)	(-0.44)	-0.81
B. Value-Weighted						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
CAPM-alpha	0.27	0.23	0.32	-0.13	-0.35	-0.62
	-2.02	-2.3	-3.48	(-1.12)	(-2.05)	(-2.34)
ICAPM-alpha	0.27	0.22	0.31	-0.11	-0.34	-0.6
	-2.03	-2.21	-3.44	(-0.95)	(-1.99)	(-2.33)
β_FMV	-0.02	-0.42	-0.53	0.88	0.62	0.64
	(-0.04)	(-0.98)	(-1.66)	-2.11	-0.73	-0.6
FF3-alpha	0.24	0.19	0.33	-0.1	-0.36	-0.6
	-1.85	-1.81	-3.58	(-0.88)	(-2.06)	(-2.30)
FF4-alpha	0.24	0.18	0.32	-0.09	-0.35	-0.59
	-1.86	-1.75	-3.58	(-0.75)	(-2.00)	(-2.29)
β_FMV	0.04	-0.3	-0.57	0.82	0.66	0.62
	-0.07	(-0.74)	(-1.78)	-1.98	-0.76	-0.55
FFC4-alpha	0.28	0.22	0.34	-0.12	-0.39	-0.67
	-2.24	-2.14	-3.73	(-1.01)	(-2.28)	(-2.66)
FFC5-alpha	0.28	0.21	0.33	-0.1	-0.38	-0.66
	-2.24	-2.06	-3.72	(-0.89)	(-2.21)	(-2.64)
β_FMV	-0.09	-0.37	-0.58	0.87	0.74	0.82
	(-0.17)	(-0.98)	(-1.90)	-2.05	-0.85	-0.74

Table 6: MAX anomaly controlled for NH (market cap-weighted).

A. Average Return						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
Low NH	0.86	1.03	1.01	0.92	-0.08	-0.94
	-1.34	-1.7	-1.57	-1.5	(-0.13)	(-2.99)
2	1.07	1.05	1.03	0.73	0.33	-0.75
	-1.73	-1.58	-1.6	-1.15	-0.46	(-3.27)
3	0.99	1.15	1.02	0.55	-0.02	-1.01
	-1.56	-1.69	-1.5	-0.84	(-0.03)	(-3.56)
4	1.2	1.19	1.22	0.48	0.59	-0.61
	-1.93	-1.85	-1.77	-0.73	-0.79	(-1.84)
High NH	1.36	1.37	1.35	0.85	0.7	-0.65
	-2.24	-1.98	-2.09	-1.2	-1.01	(-1.84)
H-L	0.49	0.35	0.34	-0.07	0.79	0.29
	-1.22	-0.91	-0.87	(-0.16)	-1.84	-0.66
B. CAPM-Alpha						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
Low NH	0.02	0.13	0.1	0	-1.01	-1.04
	-0.08	-0.54	-0.35	0	(-3.21)	(-3.17)
2	0.25	0.17	0.14	-0.19	-0.6	-0.85
	-1.35	-0.92	-0.69	(-0.85)	(-2.42)	(-4.00)
3	0.19	0.26	0.12	-0.33	-0.89	-1.08
	-1.01	-1.75	-0.64	(-1.63)	(-3.82)	(-3.58)

4	0.43	0.36	0.35	-0.41	-0.32	-0.75
	-2.36	-2.5	-1.97	(-2.40)	(-1.44)	(-2.43)
High NH	0.66	0.58	0.56	0.03	-0.15	-0.81
	-2.59	-2.44	-2.68	-0.14	(-0.64)	(-2.38)
H-L	0.64	0.45	0.47	0.03	0.86	0.22
	-1.55	-1.09	-1.14	-0.07	-1.95	-0.51
C. FF3-Alpha						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
Low NH	-0.18	-0.1	-0.1	-0.18	-1.24	-1.06
	(-0.73)	(-0.43)	(-0.39)	(-0.66)	(-4.34)	(-3.33)
2	0.08	0.01	-0.01	-0.32	-0.77	-0.85
	-0.45	-0.04	(-0.06)	(-1.56)	(-3.46)	(-4.07)
3	0.04	0.12	0.06	-0.41	-1.02	-1.07
	-0.23	-0.89	-0.33	(-1.97)	(-4.32)	(-3.50)
4	0.38	0.31	0.3	-0.43	-0.38	-0.76
	-2.25	-2.17	-1.81	(-2.41)	(-1.62)	(-2.53)
High NH	0.67	0.61	0.65	0.08	-0.1	-0.78
	-2.73	-2.64	-3.09	-0.31	(-0.43)	(-2.30)
H-L	0.86	0.7	0.75	0.26	1.14	0.28
	-2.29	-1.85	-1.92	-0.61	-2.66	-0.64
D. FFC4-Alpha						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
Low NH	-0.05	0.03	0.04	-0.02	-1.12	-1.06
	(-0.25)	-0.13	-0.15	(-0.09)	(-4.08)	(-3.30)
2	0.17	0.09	0.06	-0.25	-0.68	-0.85
	-1.05	-0.59	-0.3	(-1.30)	(-3.17)	(-4.08)
3	0.1	0.19	0.09	-0.38	-0.98	-1.08
	-0.54	-1.43	-0.52	(-1.80)	(-3.95)	(-3.50)
4	0.41	0.32	0.27	-0.48	-0.42	-0.83
	-2.5	-2.23	-1.7	(-2.69)	(-1.91)	(-2.95)
High NH	0.67	0.55	0.56	-0.03	-0.23	-0.89
	-2.68	-2.35	-3.04	(-0.11)	(-1.09)	(-2.75)
H-L	0.72	0.52	0.52	0	0.89	0.17
	-2.06	-1.44	-1.52	(-0.01)	-2.36	-0.38

Table 7: MAX anomaly controlled for NH (Equal-weighted).

FFC4-Alpha						
	Low MAX	**2**	**3**	**4**	**High MAX**	**H-L**
Low NH	0.46	0.56	0.18	0.05	-0.81	-1.27
	-2.36	-3.05	-0.88	-0.23	(-3.30)	(-5.43)
2	0.57	0.56	0.36	-0.02	-0.63	-1.2
	-3.63	-3.8	-2	(-0.12)	(-3.24)	(-7.11)
3	0.45	0.54	0.35	-0.2	-0.83	-1.28
	-2.89	-3.98	-2.45	(-1.48)	(-4.25)	(-6.67)
4	0.5	0.56	0.34	-0.19	-0.64	-1.14
	-3.29	-4.04	-2.51	(-1.30)	(-4.17)	(-6.83)
High NH	0.73	0.66	0.48	0.22	-0.69	-1.42
	-3.68	-3.63	-3.11	-1.3	(-3.60)	(-5.49)
H-L	0.26	0.1	0.3	0.17	0.11	-0.15
	-0.89	-0.39	-1.19	-0.68	-0.39	(-0.47)

Copyright © Shuai Qiao

Conclusion

This paper studies the performance of the MAX anomaly under unconditional and conditional circumstances based on data from China's A-share market from January 2000 to December 2021. During the sample period, an investment strategy of buying stocks with the highest MAX and selling stocks with the lowest MAX yields significant negative returns in the following month. This indicates that the MAX anomaly is significantly present in the Chinese stock market and remains robust after controlling for several stock characteristics. Unlike existing literature that mostly explains the MAX anomaly from the perspective of lottery-like preferences, this paper examines whether the MAX anomaly is driven by the demand to hedge overall market volatility. We construct a market-wide volatility risk factor using the volatility of comprehensive market returns and incorporate it into the benchmark pricing model to test whether it can partially explain the MAX anomaly. The results show that high MAX stocks do not have significant loadings on the volatility risk factor, and this factor can hardly explain the MAX anomaly in the Chinese market. Therefore, we rule out the possibility that high MAX stocks in the Chinese market have a hedging effect against market volatility. Observing that the MAX premium is not always negative, we attempt to explore the performance of the MAX anomaly under different conditions from the perspective of psychological thresholds. Combining the anchoring effect and psychological threshold hypothesis, we use high MAX as a proxy for potential good news for stocks and the 52-week high as investors' psychological threshold to investigate whether psychological thresholds affect investors' decision-making when faced with good news. Our empirical results show that in float market cap-weighted portfolios, investing in high MAX stocks no longer produces significant negative returns when the stock price is close to its 52- week high. To ensure the robustness of our conclusions, we have done the following: modified the definition of the variable measuring the distance from the 52-week high (NH), excluded some samples that might confuse the results, considered possible irrational behavior of investors, and used Fama-MacBeth regression to control for other stock characteristics. The results all support our hypothesis: the 52-week high as a psychological threshold affects how investors process the implicit information of high MAX, thus influencing their decisions. When the stock price is close to its 52-week high, the MAX anomaly is no longer robust. Under the influence of the psychological threshold, investors underreact to the information implied by high MAX; only when the stock price is far from its high point do they overreact to this information, leading to negative future returns. This paper verifies the general existence of the MAX anomaly based on unconditional discussions, while the exploration of the MAX anomaly under psychological thresholds indicates that investors' different reactions under different conditions may make the so-called "anomaly" no longer exist, which is an aspect that cannot be ignored in the study of market anomalies.

References

1. Bali T G, Cakici N, Whitelaw RF (2011) Maxing out: Stocks as lotteries and the cross- section of expected returns. Journal of Financial Economics 99(2): 427-446.
2. Barinov A (2018) Stocks with extreme past returns: Lotteries or insurance? Journal of Financial Economics 129(3): 458-478.
3. George TJ, Hwang CY (2004) The 52-week high and momentum investing. The Journal of Finance 59(5): 2145-2176.
4. Li J, Yu J (2012) Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics 104(2): 401-419.
5. Carhart MM (1997) On persistence in mutual fund performance. The Journal of Finance 52(1): 57-82.
6. Wan X (2018) Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market. International Review of Economics & Finance 53: 1-15.
7. Fama EF, French KR (1992) The cross-section of expected stock returns. The Journal of Finance 47(2): 427-465.
8. Jegadeesh N, Titman S (1993) Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48(1): 65-91.
9. Jegadeesh N (1990) Evidence of predictable behavior of security returns. The Journal of Finance 45(3): 881-898.
10. Amihud Y (2002) Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5(1): 31-56.
11. Ang A, Hodrick R J, Xing Y (2006) The cross-section of volatility and expected returns. The Journal of Finance 61(1): 259-299.
12. Nartea GV, Kong D, Wu J (2017) Do extreme returns matter in emerging markets? Evidence from the Chinese stock market. Journal of Banking & Finance 76: 189-197.
13. Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. Science 185(4157): 1124-1131.
14. Birru J (2015) Psychological barriers, expectational errors, and underreaction to news. Ohio State University Working Paper, USA.
15. Huang S, Lin TC, Xiang H (2021) Psychological barrier and cross-firm return predictability. Journal of Financial Economics 142(1): 338-356.
16. Driessen J, Lin TC, Van Hemert O (2013) How the 52-week high and low affect option- implied volatilities and stock return moments. Review of Finance 17(1): 369- 401.
17. Brock W, Lakonishok J, LeBaron B (1992) Simple technical trading rules and the stochastic properties of stock returns. The Journal of Finance 47(5): 1731- 1764.
18. An L, Wang H, Wang J (2020) Lottery-related anomalies: The role of reference- dependent preferences. Management Science 66(1): 473-501.
19. Annaert J, De Ceuster M, Verstegen K (2013) Are extreme returns priced in the stock market? European evidence. Journal of Banking & Finance 37(9): 3401-3411.
20. Baars M, Mohrschladt H (2021) An alternative behavioral explanation for the MAX effect. Journal of Economic Behavior & Organization 191: 868-886.
21. Barberis N, Huang M (2008) Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98(5): 2066-2100.
22. Byun SJ, Goh J, Kim DH (2020) The role of psychological barriers in lottery-related anomalies. Journal of Banking & Finance 114: 105786.
23. Cheon YH, Lee KH (2018) Maxing out globally: Individualism, investor attention, and the cross section of expected stock returns. Management Science 64(12): 5807-5831.
24. Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33(1): 3-56.
25. Fama EF, MacBeth JD (1973) Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81(3): 607-636.

Copyright © Shuai Qiao

26. Kumar A (2009) Who gambles in the stock market? The Journal of Finance 64(4): 1889-1933.

27. Nartea GV, Wu J, Liu HT (2014) Extreme returns in emerging stock markets: Evidence of a MAX effect in South Korea. Applied Financial Economics 24(6): 425- 435.

28. Newey WK, West KD (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55(3): 703-708.

29. Nguyen HT, Truong C (2018) When are extreme daily returns not lottery? At earnings announcements. Journal of Financial Markets 41: 92-116.

30. Tao R, Brooks C, Bell AR (2020) When is a MAX not the MAX? How news resolves information uncertainty. Journal of Empirical Finance 57: 33-51.

31. Tversky A, Kahneman D (1992) Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5(4): 297-323.

32. Zhong A, Gray P (2016) The MAX effect: An exploration of risk and mispricing explanations. Journal of Banking & Finance 65: 76-90.

Copyright © *Shuai Qiao*