Lottery Mindset, Mispricing and Idiosyncratic Volatility Puzzle: Evidence from the Chinese Stock Market

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Abstract

This study investigates the MAX effect regarding lottery mindset in the Chinese stock market. The MAX effect significantly affects stock returns through quintile portfolio and cross-sectional regression analyses. The most-overpriced stock groups, as categorized by mispricing index, show more support for the MAX effect. However, the idiosyncratic volatility (IVOL) effect continues regardless of consideration for the MAX effect, indicating that the MAX effect is not a source of the IVOL effect. Our results suggest that the MAX effect, which is highly relevant for overpriced stocks, might have information for determining stock price, and appears to be independent from information of the IVOL effect in the Chinese stock market.

Keywords: MAX effect, Lottery mindset, Mispricing, Idiosyncratic volatility, Emerging stock market.

JEL classification: G11; G17; G12

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Abstract

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1. Introduction

In most theoretical financial studies, investors are assumed to be rational in their decision making. To achieve better utility, investors try to construct their optimal portfolios using all available information, and should hold a well-diversified portfolio. However, Boyer, Mitton and Vorkink (2010) and Goetzmann and Kumar (2008) show that investors do not hold a well-diversified portfolio. Some studies report that investors maintain a strong priority for stocks because they apply the lottery mindset to their investment decision making. Stocks associated with this lottery mindset are documented by various kind of proxies, such as the predicted bankruptcy probability (Ohlson, 1980), the predicted failure probability (Campbell, Hilscher and Szilagyi, 2008), the expected idiosyncratic skewness (Boyer et al., 2010), the extreme positive returns in the previous month (MAX effect; Bali, Cakici and Whitelaw, 2011), and the predicted jackpot probability (Conrad, Kapadia and Xing, 2014).

Among these proxies of stocks featuring a lottery mindset, Bali et al. (2011) suggested the MAX effect as a source for explaining the idiosyncratic volatility (IVOL) puzzle. That is, the significant negative relationship between IVOL and future returns disappears after controlling for MAX in the US market. This result was supported by Annaert, De Ceuster and Verstegen (2013) for the European markets. However, Nartea, Kong and Wu (2017) and Wan (2018) found that IVOL effects remain in the Chinese stock markets after controlling for MAX. Previous studies have suggested that stocks that feature a lottery mindset resulting from the MAX effect display five interesting characteristics. The first is that an investment strategy based on the MAX effect is used more frequently on individual investors than institutional investors (Kumar, 2009; Bali et al., 2011). This result is in line with Nartea, Wu and Liu (2014), who found that the MAX effect is quite strong in emerging stock markets. The second characteristic is that stocks determined by the MAX effect seem to be chosen by investors with high gambling intention (Barber and Odean, 2008; Fong and Toh, 2014). The third is that the MAX effect reported by Bali et al. (2011) shows that high MAX stocks have firm characteristics of small size, less liquidity, higher beta, higher IVOL, and slightly higher book-to-market ratio compared to low MAX stocks. The fourth is that investor sentiment plays a critical role in driving the MAX effect (Fong and Toh, 2014). Lastly, the MAX effect is consistent with the mispricing concept, which was mentioned by Stambaugh, Yu and Yuan (2015) who firstly proposed a proxy generated using 11 anomalies for mispricing in

the U.S. stock market, and by Zhong and Gray (2016), who suggested a proxy using 7 anomalies in the Australian stock market.

On the basis of the literature related to the MAX effect, along with MIS (mispricing) and IVOL, this study empirically examines whether the MAX effect affects prices in Chinese stock markets, and the relationships among MAX, MIS and IVOL. The Chinese market provides excellent ideas for us to achieve our research goals for the following reasons. First, the Chinese stock market is representative of emerging markets, in which individual investors play an important role in transaction activities compared to the U.S. stock market (Lee, Li and Wang, 2010), who mainly drive the demand for lottery-type stocks rather than institutional investors (Kumar, 2009). According to Fong and Toh (2014), the IVOL effect is highly concentrated in stocks that are mainly owned by individual investors. Second, the Chinese market has some unique limits of arbitrage features such as price-limit rule and short-selling restrictions, that may prevent arbitrageurs from exploiting this mispricing opportunity (Gu, Kang and Xu, 2018). Moreover, the higher MAX stocks are expected to be most likely to mispricing that is not arbitraged away due to the high arbitrage risk. Added to this, Gu et al. (2018) found evidence supporting the close relationship between MIS and IVOL based on Stambaugh et al. (2015) in the Chinese stock markets. Therefore, Chinese stock markets are appropriate to investigate the MAX effect through comparison with MIS and IVOL.

The MAX effect is empirically verified by evidence that stocks with high returns in the past period have a propensity to experience a significant decline in the following period. Accordingly, testing the hypotheses in this study, we examine whether the performance of the H-L zero-cost portfolio is significantly negative, which is defined by the difference between a portfolio (H) constructed with stocks having the highest MAX and a portfolio (L) with stocks having the lowest MAX in the past period. Moreover, this study examines whether the hypothesis regarding the significant negative relationship between the MAX effect and subsequent returns is consistently observed under empirical design controlling for MIS (Stambaugh et al., 2015; Zhong and Gray, 2016) and IVOL (Ang, Hodrick, Xing and Zhang, 2006). Hence, our study extends the scope of previous studies such as Nartea et al. (2014), Nartea et al. (2017), and Gu et al. (2018) on the Chinese stock market. That is, we investigate empirically the relationship of MAX, as a signal of lottery-like characteristics, with both MIS by Stambaugh et al. (2015) and IVOL by Ang et al. (2006). This empirical design may give a new insight into the cause of the MAX effect. This can be our contribution to the literature related to MAX. From these research goals, we determine the information value of the MAX effect in Chinese stock markets. We utilize the quintile portfolio and Fama and MacBeth (1973)'s cross-sectional regression approaches. For investigating the information value of the MAX effect relative to the MIS and IVOL effects, we construct a 5 x 5 double-sorted portfolio with MIS-MAX and IVOL-MAX. As performance measures to evaluate the hypothesis, we utilize excess returns relative to the risk-free rate and the risk-adjusted return (alpha) estimated by Fama and French (1993)'s three-factor (FF3) model.

The main results are summarized as follows. The result for the MAX effect in this study is consistent with the results of previous studies; that is, the significant negative relationship between MAX and subsequent returns in the Chinese stock market. This result is robust to influential variables such as size, book-to-market, momentum, return reversals, and liquidity. Using the MIS index generated based on Stambaugh et al. (2015) and Zhong and Gray (2016), we determine that the MAX effect from the double-sorted MIS-MAX portfolio has high relevance to the mispricing, which the market price adjustment for overpriced stocks is limited by asymmetric arbitrage for investor transaction activities compared to underpriced stocks. In other words, the MAX effect has a high relevance with overpriced groups categorized by the MIS index. Interestingly, the results on the relationship between MAX and IVOL in the Chinese stock market are inconsistent with those of

Bali et al. (2011), suggesting that MAX can explain the IVOL puzzle in the U.S. stock market. On the one hand, when using the double-sorted IVOL-MAX portfolio to control for the IVOL effect, the result on the relationship between MAX and subsequent returns shows weak evidence supporting the hypothesis of a negative relationship, except for stock groups with higher IVOL. On the other hand, the negative relationship between IVOL and subsequent returns is strongly supported when using the double-sorted MAX-IVOL portfolio. That is, after controlling for MAX, we found significant evidence supporting the IVOL effect, except for stock groups with the lowest MAX. As a result, the MAX effect has high relevance with the MIS of overpriced stocks, and its information value may be accounted for as part of IVOL that has an information value in the Chinese stock market. However, the MAX effect cannot be a source of the IVOL puzzle, and the two effects appear to be independently associated with each other in the Chinese stock market. Therefore, we differentiate from the previous studies according to our focus on the effect of mispricing level, that allows stocks to be classified according to their likely degree of under/overpricing, on MAX. In fact, we successfully explore a framework to directly study whether the observed MAX effect is consistent with mispricing in the Chinese market. These findings may contribute to the literature for the MAX context. We provide a broader understanding regarding the MAX effect, especially in the Chinese stock market, determine the new relationships between MAX, IVOL, and MIS, and finally provide evidence significantly supporting that each of MAX and IVOL may have some independent information value for determining stock price in the Chinese stock market.

The remainder of this study is organized in four sections. In Section 2, we describe the data, variable construction, and methodologies utilized for our analysis. In Section 3, we present the results according to the research goals. In section 4, we conclude.

2. Data and Methodology

This study utilizes the China Stock Market Financial Statements (CSMAR) database, which contains 2,640 listed and delisted stocks from January 2000 to June 2017. We start from 2000 because of data availability. Moreover, we want to ensure that there is an adequate number of stocks to form two-way sorted portfolios that are used in our research. We select only Chinese A-shares in the Shanghai and Shenzhen exchanges. The A-shares denominated in Chinese yuan can be traded by Chinese citizens, and the A-share firms provide quarterly reports, which are essential for the construction of our mispricing index. Thus, we posit that A-shares are more representative of the Chinese market conditions to persuade our research goals. To verify our research results under the different market situations related to the effect of the economic or financial indicators, we further check the robustness of our inferences on the MAX effect along with the indifference to MIS and IVOL effects in two roughly equal sub-periods split at June 2008 based on the viewpoint of the market crash. The variable grouping in this study are as follows. Following Bali et al. (2011), MAX is defined as the highest daily return in the previous month. In all the empirical tests, the seven control variables are beta coefficient (BETA), market capitalization (SIZE) and book-to-market equity ratio (BM) from Fama and French (1992), the momentum (MOM) from Jegadeesh and Titman (1993), the short-term reversal (REV) from Huang, Liu, Rhee and Zhang (2010), liquidity (LIQ) from Chordia, Richard and Avanidhar (2001), and the price (PRICE) from Bali et al. (2011). These variables are defined in detail in Appendix A. **Table 1** reports the summary statistic of these variables such as average values and standard deviations of each variable and correlation coefficients among the variables.

Table 1
Summary Statistic

	MAX	BETA	SIZE	BM	MOM	REV	LIQ	PRICE
MEAN	0.0580	1.0963	15.0189	0.3916	0.1165	0.0158	-0.3187	12.1336
STD	0.0449	0.1499	0.8302	0.2230	0.2786	0.1200	0.2131	7.8488
MAX	1							
BETA	0.0281	1						
SIZE	-0.0583	-0.5311	1					
BM	-0.0758	-0.0601	0.0872	1				
MOM	0.0475	-0.0132	0.0291	-0.0737	1			
REV	0.3856	0.0162	-0.0292	0.0032	-0.0360	1		
LIQ	0.0414	0.0014	-0.0216	0.0876	0.0321	0.0057	1	
PRICE	0.0962	-0.1338	0.2439	-0.3579	0.2735	0.1131	-0.1597	1

Note: The table shows summary descriptive statistics for the variables employed in this paper, as follows. MAX is the highest daily return in the previous month. BETA is the firm beta. SIZE is the log firm market capitalization. BM is the book-to-market ratio. MOM is the cumulative return from the start of month *t*-7 to the end of month *t*-2. REV represents the lagged 1-month return. LIQ is the measure of liquidity. PRICE is the monthly stock price. Summary statistics include the average value and standard deviation of each variable in the first two rows and the correlations between all variables in the remaining rows.

This study establishes the hypothesis of the significant negative relationship between MAX in the past period and the following returns in the Chinese stock market. That is, the portfolio (H) constructed by stocks with the highest MAX in the previous period tends to have decreased performance in the future period, while portfolio (L) constructed by stocks with the lowest MAX in the prior period has a tendency to increased performance in the future period. Accordingly, evidence supporting the hypothesis is that the H-L zero-cost portfolio through the difference between H and L shows significant negative performance. We employ the quintile portfolio analysis and performance measurements of the excess return relative to the risk-free rate and risk-adjusted return (FF3 alpha), which are based on the FF3 model.

We conduct cross-sectional regressions of Fama and MacBeth (1973) with the dependent variable of expected excess returns relative to six past independent variables of BETA, SIZE, BM, MOM, REV, and LIQ, along with MAX in the prior period. In particular, for each month in the sample, we run the cross-sectional regression of expected excess returns in month t ($R_{j,t}$) on the MAX of month t-1 ($MAX_{j,t-1}$), together with the following six other previous month control variables ($X_{j,t-1}$): BETA, SIZE, BM, MOM, REV, and LIQ. We then report average values of cross-sectional regression coefficients estimated and t-statistics are calculated using Newey and West (1987)'s standard error to adjust for the influence of serial correlation and heteroscedasticity of residuals. The cross-sectional models are defined by,

$$R_{j,t} = \alpha_0+\beta_1 MAX_{j,t-1}+\gamma_k X_{j,t-1}+\epsilon_{j,t} \quad (1)$$

Under equation (1), we set the following 4 types of model. Model 1 consists of one independent variable: MAX. Models 2 to 7 each have two independent variables: MAX and one of six control variables, namely BETA, SIZE, BM, MOM, REV, and LIQ. Models 8 and 9 include three independent variables of BETA, SIZE, and BM and two independent variables of MOM and REV along with MAX, respectively. Model 10 consists of these six control variables and MAX. From this design of cross-sectional regression, we may verify the original pricing role of MAX under well-known control variables in the field of finance. In all models, the dependent variable is the expected excess return against the risk-free rate in the future period.

Next, this study investigates evidence supporting the MAX effect after controlling for MIS and IVOL in the Chinese stock market using a 5 x 5 double-sorted MIS-MAX portfolio and IVOL-MAX portfolio, respectively. The MIS index is generated based on Stambaugh et al. (2015) for the U.S. stock market and Zhong and Gray (2016) for the Australian stock market. In the preliminary test, we determine indicators for generating the MIS index being appropriated in the Chinese stock market among 11 anomalies by Stambaugh et al. (2015) and 7 anomalies by Zhong and Gray (2016). The result is presented in the table of Appendix B.[1] Five significant indicators are selected such as book-to-market equity ratio (BM), net operating asset (NOA), gross profitability premium (GPP), return on equity (ROE), and return on asset (ROA). Using previous studies' results of the five indicators for each stock, stocks having decreasing performance in the future against the past have a higher likelihood of being overpriced, compared to stocks having increasing performance in the future against the past. From the Chinese stock market, stocks with firm characteristics of higher BM, higher GPP, higher ROA, higher ROE and lower NOA show higher performance (as underpriced stocks), compared to stocks with firm characteristics of lower BM, lower GPP, lower ROA, lower ROE and higher NOA (as overpriced stocks). We categorize all stocks into two groups, as follows. The indicators of BM, GPP, ROA, ROE will take on a value of 1 (0) if a given indicator is below (above) its median of all stocks in that month. The indicator of NOA will take a value of 1 (0) if it is above (below) its median of all stocks in that month. Then, using a set of values assigned by 1 and 0 for each stock on the five indicators, we calculate the MIS index, which is the average value of all values from five indicators in each month. This study requires that the stock at least has two indicators in each month for generating MIS. Finally, stocks having a higher MIS are categorized into the portfolio constructed by overpriced stocks, while stocks having a lower MIS are categorized into the portfolio with underpriced stocks. In addition, IVOL is estimated by applying the FF3 model following Ang et al. (2006). Specifically, the model can be defined as below.

$$R_{i,d} = \alpha_0+\beta_1 RMRF_d + \beta_2 SMB_d+\beta_3 HML_d+\varepsilon_{i,d} \tag{2a}$$

$$IVOL_t= \sqrt{Var(\varepsilon_{i,t})}*\sqrt{D_t} \tag{2b}$$

where $R_{i,d}$ is the excess return of stock *i* against risk-free rate on the day *d*. RMRF, SMB, HML are obtained from the RESSET database which is a financial information and service provider in China. $IVOL_t$ is the monthly IVOL. D_t is the number of trading days in month t ($D_t \geq 15$). In order to extend the scope of previous studies of Nartea et al. (2017) and Gu et al. (2018), this study establishes the following hypothesis. If the MAX effect has a unique information value regardless of MIS and IVOL, the H-L MAX zero-cost portfolio within each quintile portfolio of MIS and IVOL will have a significant negative value. To test this hypothesis, we employ the following procedure. First, we divide stocks into quintile portfolios according to MIS (IVOL). Then, within each portfolio, we construct quintile portfolios by MAX. This is a 5 x 5 double-sorted MIS-MAX (IVOL-MAX) portfolio. Finally, we evaluate the hypothesis focusing on the H-L zero-cost portfolio using

[1] In the table of Appendix B, using the quintile portfolio method from each of equal and value weighting methods, we test 9 anomalies in the Chinese stock market because of data availability. That is, book-to-market ratio (BM), net operating asset (NOA), gross profitability premium (GPP), return on asset (ROA), return on equity (ROE), momentum (MOM), accruals (ACC), composite equity issues (CEI), and asset growth (AG). The table shows results of the H-L zero-cost portfolio and its risk-adjusted alpha by Fama and French (1993)'s three-factor model along with quintile portfolio returns for each anomaly. Base on the criterion of statistical significance test, we verify five significant indicators, such as book-to-market ratio (BM), net operating asset (NOA), gross profitability premium (GPP), return on equity (ROE), and return on asset (ROA). These indicators with significant evidence are in line with previous studies, e.g., Chen, Kim, Yao and Yu (2010) suggesting indicators of BM, NOA, AG, illiquidity (ILLIQ), and R&D ratio; Cakici, Chan and Topyan (2017) suggesting SIZE, BM, cash-flow-to-price (C/P), and earning-to-price (E/P).

performance measurements of the excess return and the risk-adjusted return for each quintile portfolio of MIS (IVOL).

3. Results

3.1. The MAX effect

In this section, we present the results on the MAX effect in the Chinese stock market in **Table 2**. The table shows average monthly excess returns relative to risk-free rate (Ex.Ret) and risk-adjusted return of the FF3 model (FF3 alpha) for quintile portfolio using equal-weighted (EW) and value-weighted (VW) returns. The performance of the H-L zero-cost portfolio, which is the difference between the highest portfolio (H) and the lowest portfolio (L), is presented in the last row of the table.

Table 2
MAX effect in the Chinese stock market

	value-weighting		equal-weighting	
	Ex.Ret	FF3 alpha	Ex.Ret	FF3 alpha
Lowest	0.0086	0.0005	0.0183[c]	0.0049[c]
	(1.06)	(0.20)	(1.94)	(1.78)
2	0.0103	0.0012	0.0176[b]	0.0037[b]
	(1.27)	(0.66)	(1.99)	(2.17)
3	0.0129	0.0051[b]	0.0160[c]	0.0028[b]
	(1.55)	(2.45)	(1.82)	(2.02)
4	0.0041	-0.0028[c]	0.0109	-0.0013
	(0.49)	(-1.85)	(1.28)	(-0.88)
Highest	0.0027	-0.0061	0.0075	-0.0052[a]
	(0.30)	(-2.75)[a]	(0.83)	(-2.62)
H-L	-0.0059[c]	-0.0067[b]	-0.0109[a]	-0.0100[a]
	(-1.87)	(-1.97)	(-5.57)	(-3.89)

Note: The table shows results on the MAX effect using quintile portfolios in the Chinese stock market. For VW (the first two columns) and EW (the last two columns) schemes, performance measurements are divided into the excess return (Ex.Ret) and the FF3 model alpha (FF3 alpha) for each quintile portfolio. The H-L zero-cost portfolio in the last row presents the difference between the highest (H) and lowest (L) portfolios. Parentheses are t-values based on Newey-West (1987), and 'a', 'b', and 'c' are the significance levels of '1%', '5%', and '10%', respectively.

Table 2 presents evidence supporting the MAX effect in the Chinese stock market. That is, the VW (EW) excess return of the H-L zero-cost portfolio is -0.0059 (-0.0109) with a t-statistic of -1.87 (-5.57), and the VW (EW) risk-adjusted return of the H-L zero-cost portfolio is -0.0067 (-0.0100) with a t-statistic of -1.97 (-3.89). This result is consistent with Bali et al. (2011) for evidence of the MAX effect in the US market, as well as with Nartea et al. (2017) and Wan (2018) for evidence of the MAX effect in the Chinese stock market. In addition, the MAX effect is stronger in the EW portfolio than in the VW portfolio. The possible explanations from previous studies are as follows. Fong and Toh (2014) provide evidence on the negative MAX effect that exists in lower ownership of institutional investors, like small firms. This is consistent with the general characteristics of emerging stock markets in which individual investors play an important role in transaction activities. As mention previously, the Chinese stock market is dominated by retail investors, who largely drive the demand for lottery-type stocks (Kumar, 2009; Lee et al., 2010). Thus, the Chinese stock market provides

an ideal setting to study the MAX effect as a proxy of lottery-like stock features. Additionally, our findings deliver useful out-of-sample empirical evidence that may lead to a better understanding of the MAX effect characteristics across the stock markets. In addition, **Table 3** shows the characteristics of firm-specific variables for each MAX quintile portfolio using VW and EW returns. According to the results, high-MAX stocks in the Chinese stock market include the characteristics of higher BETA, smaller SIZE, lower BM, higher MOM, higher REV, higher LIQ, and higher PRICE than low-MAX stocks, consistent with Bali et al. (2011) for the US market, except for price. The U.S. stock market shows that the high-MAX stocks tend to have lower price compared to the low-MAX stocks. This differential result between the markets can be explained by the difference in the culture as explained by the cross-country variation in the MAX phenomenon (Cheon and Lee, 2018). This argument is also in line with the finding of Annaert et al. (2014), who mentioned that the MAX effect depends on the local market return.

Table 3
Firm characteristics of MAX quintile portfolios

	MAX	BETA	SIZE	BM	MOM	REV	LIQ	PRICE
Panel A: value-weighting scheme								
Lowest	0.0296	0.9888	16.9892	0.5355	0.0692	-0.0284	-2.2826	14.1273
2	0.0469	1.0041	16.5982	0.4407	0.1493	-0.0077	-1.8713	16.9689
3	0.0574	1.0173	16.4642	0.4117	0.2188	0.0179	-1.7750	18.1362
4	0.0724	1.0139	16.3955	0.3842	0.2844	0.0613	-1.7350	19.4468
Highest	0.1208	1.0249	16.2230	0.4306	0.3132	0.1304	-1.6599	18.5505
Panel B: equal-weighting scheme								
Lowest	0.0298	1.0867	15.2012	0.4522	0.0774	-0.0309	-1.7729	11.0809
2	0.0420	1.0967	15.0972	0.4146	0.0917	-0.0126	-1.6553	11.7288
3	0.0525	1.0982	15.0814	0.3894	0.1182	0.0066	-1.6243	12.5162
4	0.0662	1.0971	15.0829	0.3721	0.1547	0.0357	-1.6167	13.8158
Highest	0.1020	1.1034	15.0159	0.3846	0.1588	0.0928	-1.5838	13.4177

Note: The table reports the firm characteristics for each quintile portfolio formed by MAX. Results are divided by weighting schemes of VW (Panel A) and EW (Panel B) returns. Average values are reported on MAX, BETA, SIZE, BM, MOM, REV, LIQ, and PRICE.

Next, results on the cross-sectional regression of the MAX effect are presented in **Table 4**. We employ ten models based on Fama and MacBeth's cross-sectional regression. In regression analysis, the dependent variable is the excess return of each stock in the future period, and independent variables estimated from the past period are influential variables of BETA, SIZE, BM, MOM, REV, and LIQ, along with MAX. For each month, we estimate the regression coefficients, and then report the average values of all regression coefficients estimated during the whole period.

Table 4
Cross-sectional regression

Model	MAX	BETA	SIZE	BM	MOM	REV	LIQ
1	-0.0859[b] (-2.19)						
2	-0.2057[a] (-6.70)	0.0181[a] (3.23)					
3	-0.2008[a]		-0.0057[a]				

	(-7.71)		(-3.00)				
4	-0.2061[a]			0.0058			
	(-6.81)			(1.27)			
5	-0.1999[a]				-0.0038		
	(-6.63)				(-0.71)		
6	-0.2266[a]					0.0068	
	(-6.21)					(0.62)	
7	-0.2003[a]						-0.0001
	(-6.20)						(-0.07)
8	-0.2165[a]	0.0002	-0.0056[a]	0.0063[c]			
	(-7.29)	(0.09)	(-3.17)	(1.66)			
9	-0.2244[a]				-0.0038	0.0068	
	(-6.51)				(-0.72)	(0.61)	
10	-0.2077[a]	0.0002	-0.0068[a]	0.0047	-0.0067	-0.0106	-0.0058[a]
	(-6.65)	(0.09)	(-3.53)	(1.21)	(-1.28)	(-0.89)	(-5.58)

Note: The table presents the results on the MAX effect from the cross-sectional regression based on Fama and MacBeth (1973). The dependent variable is the excess return in the future period. Independent variables estimated from the past period are MAX, as well as well-known control variables of firm beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), and liquidity (LIQ). Cross-sectional regression is conducted in each month during the whole period, and then all regression coefficients for each independent variable are averaged. Parentheses are t-values based on Newey-West (1987), and 'a', 'b', and 'c' are the significance levels of '1%', '5%', and '10%', respectively.

In **Table 4**, the cross-sectional regression results present statistically significant evidence supporting the MAX effect regardless of which influential variables are included in the model. Model 1 including only MAX as an independent variable, detects a significant negative relationship between MAX and future returns. Similar results are also obtained when BETA (Model 2), SIZE (Model 3), BM (Model 4), MOM (Model 5), REV (Model 6), and LIQ (Model 7) are individually included in the models as the control variable. In these models, the regression coefficient on MAX remains negative and statistically significant. Also, when either three variables, namely BETA, SIZE and BM (Model 8), or two variables, namely MOM and REV (Model 9), are added as the control variables, the results identically present evidence supporting the strong negative MAX effect. When all control variables, along with MAX, are simultaneously included in Model 10, the model has a significant negative coefficient, which supports our hypothesis of the MAX effect. Therefore, these results suggest that the MAX effect is priced in the Chinese stock market regardless of controlling for well-known control variables in the field of finance. Further, these results are qualitatively the same with those of **Table 2**. Consequently, we determine that the MAX effect existed and exerted a significant effect in the Chinese stock market from January 2000 to June 2017. This is consistent with previous studies of Bali et al. (2011) for the US market, and of Nartea et al. (2017) and Wan (2018), who show the presence of a negative MAX in the Chinese stock market.

3.2. Relationship of MAX with the mispricing and the idiosyncratic volatility

In this section, we present the results on the effects of MIS and IVOL on the MAX effect. First, this study investigates whether the MAX effect in the Chinese stock market has a close relationship with MIS, as suggested by Stambaugh et al. (2015). Arbitrage transactions are followed by the mispricing events (Pontiff, 2006). The overpriced stocks in the past period tend to have slowly decreasing values in the future period because of the short-sale constraint in the market, compared to the underpriced stocks by buying trades. By using a double-sorted MIS-MAX portfolio, we verify that the H-L MAX zero-cost portfolio has a significant

negative value within MIS quintile portfolios. If the overpriced stocks are deterred from the asymmetric arbitrage caused by the short-sale constraint, the H-L MAX zero-cost portfolio has strong supportive evidence within the higher MIS portfolio, compared to the lower MIS portfolio. Next, we examine the information value of MAX by comparison with IVOL based on previous studies; for example, Bali et al. (2011) found that MAX explains the IVOL puzzle in the US stock market. For obtaining robust results on the relationship between MAX and IVOL in the Chinese stock market, we utilize both double-sorted IVOL-MAX and MAX-IVOL portfolios. That is, we determine which effect may be dominant over the other effect or whether the information value will be independent with each other.

The results on the relationship between MAX and MIS are presented in **Table 5**. For our research goal, we generated the MIS index based on Stambaugh et al. (2015) and Zhong and Gray (2016). Using the MIS index, a stock is defined as overpriced or underpriced in the past; that is, stocks with a higher or lower MIS index are categorized into the overpriced or underpriced stocks group, respectively. Based on the double-sorted MIS-MAX portfolio method, we investigate the influence of MIS on the MAX effect. Subsequently, we evaluated the hypothesis of MAX under each MIS quintile portfolio as the categorized overpriced and underpriced stock groups. The table reports the performance of the excess returns and the risk-adjusted return (FF3 alpha) using VW and EW returns. In the last row of the table, we also report the average values of all MIS quintile portfolios in each MAX portfolio. This presents evidence of the MAX effect after considering the difference of the MIS quintile portfolios.

Table 5
Double-sorted MIS-MAX portfolio

	Lowest MAX	2	3	4	Highest MAX	H-L	FF3 alpha
Panel A: value-weighting scheme							
Lowest MIS	0.0129	0.0176	0.0182	0.012	0.0083	-0.0046 (-0.59)	-0.0042 (-1.10)
2	0.0097	0.0136	0.0138	0.0078	0.0046	-0.0051 (-1.17)	-0.0053 (-1.27)
3	0.0074	0.0081	0.0085	0.0071	-0.0004	-0.0078 (-1.34)	-0.0101[c] (-1.79)
4	0.0082	0.0094	0.0081	0.0025	-0.0023	-0.0105[a] (-3.59)	-0.0107[a] (-3.27)
Highest MIS	0.0082	0.0074	0.0062	0.0007	-0.0026	-0.0108[a] (-3.56)	-0.0115[a] (-3.80)
AVE						-0.0078[a] (-2.93)	-0.0084[a] (-3.02)
Panel B: equal-weighting scheme							
Lowest MIS	0.0206	0.0216	0.0213	0.017	0.0124	-0.0082[a] (-3.54)	-0.0068[a] (-2.95)
2	0.0172	0.0199	0.0166	0.013	0.0088	-0.0084[a] (-3.99)	-0.0081[a] (-3.38)
3	0.0144	0.0151	0.0135	0.0099	0.0042	-0.0102[a] (-2.79)	-0.0107[a] (-2.66)
4	0.0145	0.0153	0.0119	0.0067	0.0021	-0.0124[a] (-5.20)	-0.0118[a] (-4.39)
Highest MIS	0.0115	0.0114	0.0113	0.0041	-0.0009	-0.0124[a] (-5.97)	-0.0125[a] (-5.14)
AVE						-0.0103[a] (-5.90)	-0.0100[a] (-4.81)

Note: The table shows results on the MAX effect after controlling for MIS (mispricing) through the double-sorted MIS-MAX portfolio. Each month, all stocks are sorted into the quintile portfolio based on MIS, and within each portfolio, stocks are sorted into the quintile portfolio based on MAX. Results are divided by weighting schemes of VW (Panel A and EW (Panel B) returns. The last two columns show results on the H-L MAX zero-cost portfolios by excess returns and risk-adjusted returns (FF3 alpha). In the last row of each panel, average values (AVE) of all MIS portfolios are presented for each MAX portfolio. Parentheses are t-values based on Newey-West (1987), and 'a', 'b', and 'c' are the significance levels of '1%', '5%', and '10%', respectively.

Table 5 reports that the MAX effect in the Chinese stock market is more evident under MIS with overpriced stocks. In Panel A using the VW scheme, the H-L MAX zero-cost portfolios within the higher MIS portfolios have significant excess returns and significant risk-adjusted returns, while the H-L MAX zero-cost portfolios in Panel B using the EW scheme have all significant values in the quintile portfolio. That is, the EW scheme presents more obvious evidence to support the MAX effect, compared to the VW scheme. These results suggest that the MAX effect has a high relevance with the overpriced group categorized by the MIS index, regardless of the weighting schemes. In addition, in the last row containing the average values of excess returns of all MIS portfolios in each MAX quintile portfolio, the H-L MAX portfolio by VW (EW) returns has significant excess returns of -0.0078 (-0.0103) with a t-statistic of -2.93 (-5.90), and significant risk-adjusted returns of -0.0084 (-0.0100) with a t-statistic of -3.02 (-4.81). This represents evidence supporting the MAX effect after considering the difference of the MIS quintile portfolios. Therefore, the MAX effect has a high relevance with overpriced stocks, which from the perspective of Stambaugh et al. (2015) may be caused by the asymmetric arbitrage trading, suggesting that investor transactions of overpriced stocks are prevented due to the short-sale constraint compared to the underpriced stocks. Our findings are in line with Cao and Han's (2016) report that MAX is associated with higher arbitrage costs, and the arbitrageurs will take smaller positions in these stocks, leading to their lower contribution to the correcting mispricing. Thus, due to costly arbitrage, the high MAX stocks are expected to be the most-susceptible to mispricing that is not arbitraged away, since high levels of arbitrage risk deter investors from entering the short positions in high MAX stocks that are necessary to correct the overpricing. Meanwhile, as the low MAX stocks may be underpriced, investors can take sufficiently large long positions to correct the mispricing because they are not constrained in the same way they are with short sales. Consequently, this evidence is consistent with the mispricing explanation showing that the MAX anomaly is stronger among stocks potentially the most short-sale-constrained. Moreover, given arbitrage asymmetry, the magnitude of the MAX effect amongst overpriced stocks exceeds that amongst underpriced, resulting in an overall negative relation that has been well documented.

Next, **Table 6** reports the results from investigating whether the MAX effect has the information value after controlling for IVOL in the Chinese stock market. We also utilize the double-sorted portfolio by MAX and IVOL. The table separately shows the results of Panel A for the IVOL-MAX portfolio and of Panel B for the MAX-IVOL portfolio according to the research design to obtain robust results. The double-sorted portfolio is constructed as follows: we first sorted all stocks into quintile portfolios based on IVOL (MAX), and then within each portfolio, we sorted stocks into quintile portfolios based the IVOL-MAX (MAX-IVOL) portfolios. The table presents the excess returns and risk-adjusted returns using both VW and EW returns in each panel. Furthermore, in the last row of each panel, we report average values computed from all IVOL (MAX) quintile portfolios in each MAX (IVOL) quintile portfolio.

Table 6
Relationship between MAX and IVOL

Panel A: IVOL-MAX portfolio							
	Lowest MAX	2	3	4	Highest MAX	H-L	FF3 alpha
using value-weighting scheme							
Lowest IVOL	0.0113	0.0177	0.0208	0.0212	0.0205	0.0092[a] (3.32)	0.0075[a] (3.05)
2	0.0161	0.0179	0.0183	0.0184	0.0171	0.0010 (0.48)	0.0006 (0.28)
3	0.0140	0.0134	0.0150	0.0153	0.0145	0.0005 (0.27)	0.0017 (0.82)
4	0.0150	0.0093	0.0097	0.0090	0.0075	-0.0075[a] (-3.59)	-0.0073[a] (-3.12)
Highest IVOL	0.0059	0.0042	0.0000	-0.0012	-0.0011	-0.0070[b] (-2.39)	-0.0087[a] (-2.95)
AVE						-0.0008 (-0.53)	-0.0012 (-0.80)
using equal-weighting scheme							
Lowest IVOL	0.0118	0.0181	0.0211	0.0216	0.0210	0.0092[a] (3.34)	0.0073[a] (3.04)
2	0.0164	0.0182	0.0187	0.0187	0.0174	0.0010 (0.49)	0.0006 (0.28)
3	0.0143	0.0137	0.0152	0.0154	0.0148	0.0005 (0.26)	0.0016 (0.80)
4	0.0153	0.0096	0.0099	0.0091	0.0077	-0.0076[a] (-3.63)	-0.0073[a] (-3.13)
Highest IVOL	0.0060	0.0042	0.000	-0.0011	-0.0010	-0.0070[b] (-2.41)	-0.0087[a] (-2.90)
AVE						-0.0008 (-0.56)	-0.0013 (-0.82)
Panel B: MAX-IVOL portfolio							
	Lowest IVOL	2	3	4	Highest IVOL	H-L	FF3 alpha
using value-weighting scheme							
Lowest MAX	0.0156	0.0158	0.0163	0.0159	0.0142	-0.0014 (-0.53)	-0.0025 (-1.03)
2	0.0204	0.0179	0.0180	0.0136	0.0145	-0.0059[a] (-2.91)	-0.0054[a] (-2.75)
3	0.0209	0.0187	0.0141	0.0127	0.0075	-0.0134[a] (-5.72)	-0.0120[a] (-5.29)
4	0.0197	0.0133	0.0116	0.0062	-0.0004	-0.0201[a] (-6.80)	-0.0197[a] (-6.54)
Highest MAX	0.0135	0.0095	0.0032	0.0012	-0.0044	-0.0179[a] (-6.11)	-0.0154[a] (-5.75)
AVE						-0.0117[a] (-6.81)	-0.0110[a] (-6.71)
using equal-weighting scheme							
Lowest MAX	0.0161	0.0162	0.0167	0.0162	0.0145	-0.0016 (-0.65)	-0.0028 (-1.15)
2	0.0209	0.0183	0.0182	0.0138	0.0147	-0.0062[a] (-3.06)	-0.0057[a] (-2.90)
3	0.0213	0.0189	0.0143	0.0129	0.0077	-0.0136[a] (-5.76)	-0.0121[a] (-5.35)

4	0.0200	0.0137	0.0118	0.0064	-0.0002	-0.0202[a] (-6.82)	-0.0198[a] (-6.55)
Highest MAX	0.0137	0.0096	0.0032	0.0013	-0.0043	-0.0180[a] (-6.19)	-0.0155[a] (-5.80)
AVE						-0.0119[a] (-6.93)	-0.0112[a] (-6.80)

Note: The table reports results on the relationship between MAX and IVOL in the Chinese stock market. Each month, all stocks are sorted into the quintile portfolio based on IVOL (MAX), and within each portfolio, stocks are sorted into the quintile portfolio based on MAX (IVOL). That is, the double-sorted IVOL-MAX (MAX-IVOL) portfolio. Panels A and B are for the IVOL-MAX and MAX-IVOL portfolios, respectively. In each panel, results are divided by using VW and EW returns. The last two columns show results on the H-L MAX (IVOL) zero-cost portfolios for each IVOL (MAX) quintile portfolio in Panel A (B) by excess returns and risk-adjusted returns (FF3 alpha). In the last rows in each result, average values (AVE) are for all MAX (IVOL) portfolios in each IVOL (MAX) portfolio of Panel A (B). Parentheses are t-values based on Newey-West (1987), and 'a', 'b', and 'c' are the significance levels of '1%', '5%', and '10%', respectively.

According to the results of the IVOL-MAX portfolios in Panel A, we verify weak evidence supporting the MAX effect when controlling for IVOL, except within the higher IVOL portfolios, regardless of weighting schemes. That is, the MAX effect can be observed in higher IVOL quintile portfolios. The H-L MAX zero-cost portfolio by VW (EW) returns within the highest IVOL portfolio has a significant excess return of -0.0070 (-0.0070) with a t-statistic of -2.39 (-2.41) and a significant risk-adjusted return of -0.0087 (-0.0087) with a t-statistic of -2.95 (-2.90). In contrast, results in the lowest IVOL portfolios by the VW (EW) returns show significant positive performance of an excess return of 0.0092 (0.0092) with a t-statistic of 3.32 (3.34), and a risk-adjusted return of 0.0075 (0.0073) with a t-statistic of 3.05 (3.04). Consequently, these results cannot provide strong evidence supporting that the MAX effect has the information value for determining stock price regardless of considering IVOL in the Chinese stock market. In addition, we verify the results on the MAX-IVOL portfolio in Panel B of **Table 6**. The evidence supporting the IVOL effect from Ang et al. (2006) is the significant negative performance of the H-L zero-cost IVOL portfolio after controlling for MAX. Regardless of weighting schemes, the table shows that the results of excess returns and risk-adjusted return are definitely significant negative values, except within the lowest MAX portfolio. Further, the average values computed from the MAX quintile portfolios in each IVOL quintile portfolio present supportive evidence for IVOL. The results of Panel B support that the IVOL effect has the information value for determining stock price under independent relationship with the MAX effect in the Chinese stock market. Accordingly, the MAX effect cannot be a source of the IVOL puzzle in the Chinese market. However, each of MAX and IVOL may have some independent information value for determining stock price in the Chinese stock market.

3.3. Robustness

In this section, we further verify the robustness of our results on the MAX effect along with the MIS and IVOL in the two-type sub-period split at June 2008. From the viewpoint of the market crash, we posit that it's better to divide the whole period into 2-type sub-periods: (normal market) 2000.01-2008.06, and (market crisis) 2008.07-2017.06, which includes the 2008-2009 sub-prime mortgage crises, 2011-2012 European sovereign crisis, and 2015-2016, invisible economic decline. The procedure is the same as that in **Tables 5** and **6** for each relationship between MAX and MIS and between MAX and IVOL in the two-type sub-periods. **Table 7** reports the results of the H-L zero-cost portfolios for the MAX-MIS portfolios, MAX-IVOL portfolios, and

IVOL-MAX portfolios over periods of January 2000 to June 2008 (Panel A) and July 2008 to June 2017 (Panel B), respectively.

Table 7

MIS-MAX, IVOL-MAX and MAX-IVOL double-sorted portfolios in two-type sub-periods

	MIS-MAX				IVOL-MAX				MAX-IVOL			
	VW		EW		VW		EW		VW		EW	
	H-L	FF3 alpha	H-L	FF3 alpha	H-L	FF3 alpha	H-L	FF3 alpha	H-L	FF3 alpha	H-L	FF3 alpha
Panel A: January 2000 to June 2008												
Lowest	-0.0032	-0.0018	-0.0028	-0.0016	0.0104[b]	0.0095[a]	0.0038	0.0038	0.0012	0.0027	-0.0026	-0.0030
	(-0.76)	(-0.37)	(-1.14)	(-0.47)	(2.08)	(3.06)	(1.24)	(1.28)	(0.17)	(0.43)	(-1.09)	(-0.83)
2	-0.0088[c]	-0.0091	-0.0091[b]	-0.0098[c]	-0.0038	-0.0048	-0.0017	-0.0002	-0.0038	-0.0023	0.0014	0.0043
	(-1.67)	(-1.37)	(-2.16)	(-1.65)	(-0.96)	(-0.85)	(-0.70)	(-1.24)	(-0.68)	(-0.43)	(0.35)	(1.20)
3	-0.0186[b]	-0.0170[c]	-0.0195[a]	-0.0135[b]	-0.0026	-0.0022	-0.0019	-0.0027	-0.0141[a]	-0.0120[a]	-0.0164[a]	-0.0126[a]
	(-2.05)	(-1.69)	(-4.01)	(-2.32)	(-0.56)	(-0.52)	(-0.81)	(-0.10)	(-3.59)	(-2.94)	(-4.15)	(-3.02)
4	-0.0124[a]	-0.0134[a]	-0.0196[a]	-0.0189[a]	-0.0082[c]	-0.0082[c]	-0.0087[a]	-0.0087[a]	-0.0162[a]	-0.0140[a]	-0.0212[a]	-0.0189[a]
	(-4.55)	(-3.33)	(-4.12)	(-3.38)	(-1.93)	(-1.92)	(-3.11)	(-2.81)	(-2.98)	(-2.66)	(-3.57)	(-2.86)
Highest	-0.0131[a]	-0.0106[b]	-0.0143[a]	-0.0124[b]	-0.0077	-0.0090[c]	-0.0102[a]	-0.0117[b]	-0.0118[c]	-0.0085	-0.0174[a]	-0.0128[a]
	(-3.73)	(-2.50)	(-3.52)	(-2.35)	(-1.53)	(-1.73)	(-2.66)	(-2.51)	(-1.93)	(-1.51)	(-3.17)	(-2.82)
AVE	-0.0112[a]	-0.0104[b]	-0.0131[a]	-0.0112[b]	-0.0024	-0.0029	-0.0037[c]	-0.0039	-0.0089[a]	-0.0068[b]	-0.0112[a]	-0.0086[a]
	(-3.13)	(-2.12)	(-3.56)	(-2.25)	(-0.75)	(-1.01)	(-1.70)	(-1.23)	(-3.24)	(-2.17)	(-5.02)	(-3.04)
Panel B: July 2008 to June 2017												
Lowest	-0.0114	-0.0087	-0.0208[a]	-0.0145[a]	0.0054	0.0056	0.0088[b]	0.0108[a]	-0.0006	-0.0061	-0.0056	-0.0059[c]
	(-1.22)	(-1.44)	(-5.34)	(-3.99)	(1.05)	(1.12)	(2.17)	(2.80)	(-0.10)	(-0.84)	(-1.27)	(-1.81)
2	-0.0039	-0.0083	-0.0111[a]	-0.0087[b]	-0.0009	-0.0012	0.0040	0.0049[c]	-0.0003	-0.0012	-0.0053	-0.0001
	(-0.62)	(-1.33)	(-3.04)	(-2.07)	(-0.17)	(-0.26)	(1.59)	(1.76)	(-0.07)	(-0.26)	(-1.07)	(-0.02)
3	0.0032	-0.0045	-0.0066[b]	-0.0070[c]	0.0007	0.0024	-0.0009	0.0033	-0.0094[b]	-0.0121[b]	-0.0091[b]	-0.0082[b]
	(0.41)	(-0.51)	(-2.00)	(-1.77)	(0.17)	(0.54)	(-0.36)	(1.19)	(-2.37)	(-2.42)	(-2.42)	(-2.00)
4	-0.0109[b]	-0.0090	-0.0129[a]	-0.0071[c]	-0.0010	-0.0025	-0.0062[b]	-0.0038	-0.0092[c]	-0.0149[a]	-0.0172[a]	-0.0163[a]
	(-2.44)	(-1.36)	(-3.77)	(-1.85)	(-0.25)	(-0.41)	(-2.45)	(-1.26)	(-1.86)	(-2.76)	(-4.95)	(-4.02)
Highest	-0.0103[b]	-0.0109[b]	-0.0142[a]	-0.0115[a]	-0.0092[b]	-0.0116	-0.0161[a]	-0.0207[c]	-0.0180[a]	-0.0199[a]	-0.0189[a]	-0.0177[a]
	(-2.53)	(-2.21)	(-4.68)	(-2.93)	(-2.23)	(-1.59)	(-2.65)	(-1.86)	(-3.06)	(-3.07)	(-4.88)	(-3.88)
AVE	-0.0067[c]	-0.0083[c]	-0.0131[a]	-0.0098[a]	-0.0010	-0.0015	-0.0021	-0.0011	-0.0075[b]	-0.0108[a]	-0.0112[a]	-0.0096[a]
	(-1.85)	(-1.94)	(-4.99)	(-3.19)	(-0.42)	(-0.41)	(-1.06)	(-0.34)	(-1.99)	(-2.75)	(-3.73)	(-3.24)

Note: This table shows the results of the double-sorted MIS-MAX, IVOL-MAX, and MAX-IVOL portfolios for the two roughly equal sub-periods split at June 2008 (January 2000 - June 2008 in Panel A, July 2008 - June 2017 in Panel B). Specifically, we present the H-L zero-cost portfolio of interest variables by excess returns and risk-adjusted returns (FF3 alpha) within each quintile portfolio of the control variables in both EW and VW. For the MIS-MAX portfolio, we present the H-L zero-cost portfolio of MAX within each quintile portfolio of MIS in both EW and VW. For IVOL-MAX (MAX-IVOL) portfolio, we present the H-L zero-cost portfolio of MAX (IVOL) within each quintile portfolio of IVOL (MAX) in both EW and VW. In the last row of each panel, average values (AVE) of all MIS, (IVOL, MAX) portfolios are presented for each MAX (MAX, IVOL) portfolio, respectively. Parentheses are t-values based on Newey-West (1987), and 'a', 'b', and 'c' are the significance levels of '1%', '5%', and '10%', respectively.

In **Table 7**, we verify that the results are qualitatively similar between the two-type sub-periods, and also with the previous results. In each sub-period, the return spreads between high and low MAX stocks are significantly and insignificantly negative for overvalued and undervalued stocks, respectively. Additionally, the independence of the MAX and IVOL effects is also confirmed in the Chinese stock market. The main findings are as follows. For results from the MIS-MAX double-sorted portfolios, the MAX in Panel A over period from January 2000 to June 2008 has significant excess returns and risk-adjusted returns (FF3 alpha) in the highest MIS, as defined by the overpriced stock group, regardless of weighting schemes. Further, we find a significant negative MAX effect in Panel B over the period from July 2008 to June 2017. These results are consistent with the previous results, in which the MAX effect has high relevance to the overpriced stocks. Second, we investigate the MAX effect after controlling for IVOL using IVOL-MAX double-sorted portfolios in each sub-period. As confirmed in the previous results, MAX is priced in the high IVOL portfolios. In the EW scheme, MAX has a significant negative excess returns and risk-adjusted returns (FF3 alpha) of the H-L MAX zero-cost portfolio. The results using the VW scheme present slightly weaker evidence, compared to those using the EW scheme. Finally, we examine the IVOL effect after controlling for MAX using the MAX-IVOL double-sorted portfolios. Regardless of weighting schemes, the IVOL effect presents significant evidence in the higher MAX portfolios. Further, these results support that the IVOL effect is more evident in the Chinese stock market, compared to the MAX effect. Also, that the MAX effect has different information value to the IVOL effect in this stock market, unlike the US stock market. Therefore, this study determines that the MAX effect in the relationship with MIS and IVOL documented in Section 3.2. is qualitatively robust in the two-type sub-period having different market situations in the middle of market crashes.

3.4. Discussion

From the previous results, this study determines that the MAX and IVOL effects can be independently priced in the Chinese stock market. That is, the MAX effect is not a source of the IVOL effect, unlike Bali et al. (2011)'s finding for the US stock market. Accordingly, this section presents our findings that differ from those of the previous studies investigating the Chinese stock market such as Nartea et al. (2017) and Gu et al. (2018), and also some possible explanations for the difference from Bali et al. (2011)'s investigation of the US stock market.

First of all, our study makes a different contribution to the findings of Nartea et al. (2017) and Gu et al. (2018) from the perspectives of both empirical findings and empirical designs. First, from the perspective of empirical findings, our study differs by directly investigating the relationship between MAX and MIS under the methodology created by Stambaugh et al. (2015) who propose a proxy for mispricing that allows stocks to be classified according to their likely degree of under/overpricing. We found that the MAX effect has high relevance to the overpriced stocks categorized by the higher MIS index. These results may provide new insight into the cause of the MAX effect, with strong evidence that it results from a mispricing concept. In terms of the empirical design, we successfully explore a framework to directly study whether the observed MAX effect is consistent with mispricing applying in the Chinese market. In the spirit of Stambaugh et al. (2015), we construct a mispricing proxy by combining the existence of the return on anomalies in the Chinese market; that is, the MIS index is devised using five significant anomalies in the Chinese stock market. From the double-sorted MIS-MAX portfolio analysis, we determine that the MAX effect has high relevance with overpriced stocks categorized by the MIS index, which can be explained by asymmetric arbitrage. This empirical finding is not mentioned in the findings of Nartea et al. (2017) or of Gu et al. (2018). Second, our empirical test is conducted more robustly to examine the MAX (IVOL) effect after controlling for IVOL (MAX). On the one hand, based on the MAX-IVOL, the result presents evidence supporting that the MAX effect has the

information value for determining stock price within higher IVOL in the Chinese stock market. On the other hand, based on MAX-IVOL, we confirm that the IVOL effect has the information value for determining stock price under an independent relationship with the MAX effect in the Chinese stock market. Accordingly, these results suggest that each of MAX and IVOL may have some independent information value for determining stock price in the Chinese stock market. This finding was not reported in Nartea et al. (2017). Consequently, we believe that our study extends the contributions from the previous studies, such as Nartea et al. (2017) and Gu et al. (2018), in investigating the Chinese stock market.

Next, our findings related to the relationship between MAX and IVOL are different from those of Bali et al. (2011), who suggested that the IVOL effect can be driven by the MAX effect in the US market. Based on the previous studies, we attribute this difference to the following reasons. First, Cheon and Lee (2018) ascribe the difference to the culture explaining the cross-country variation in the pricing of MAX. They provided evidence showing the existence of a larger premium for lottery-type stocks in high individualism countries, such as the US, rather than in low individualism countries, such as China. Second, in the context of lottery-type stocks, Kumar (2009) shows that investors appear to exhibit a preference for lottery-type stocks, which he defines as low-priced stocks with high IVOL and high idiosyncratic skewness. Similarly, Bali et al. (2011) reveal that the typical high-MAX firm has a lower share price and higher IVOL than the typical low-MAX firm has in the US stock market. However, as confirmed from the previous results of **Table 3**, high-MAX stocks in the Chinese stock market have a higher price than low-MAX stocks have. Hence, the firm characteristics may cause the difference between the U.S. and Chinese stock markets. This suggestion is supported by Egginton and Hur (2018), who mention that the IVOL puzzle is robust after controlling for MAX when using a sample with a $5 price restriction in the US market. Third, the IVOL effect has a strong relevance with the transaction activity of individual investors (Han and Kumar, 2008). Trading activities in the Chinese stock market appear to be strongly affected by individual investors, who are potentially subject to significant biases relative to sophisticated institutional investors (Ng and Wu, 2006; Lee et al., 2010). Therefore, the IVOL effect may be stronger in the Chinese stock market than in the U.S. stock market. Based on suggestions from the previous studies, the MAX effect cannot be a source of the IVOL puzzle and, moreover, the MAX and IVOL effects may independently affect the changes of stock returns in the Chinese stock market.

4. Conclusion

In this study, we empirically investigate the MAX effect regarding the lottery mindset, while also considering the MIS and IVOL effects using Chinese A-shares in the Shanghai and Shenzhen exchanges from January 2000 to June 2017. Our study findings present strong evidence of a significantly negative relation between the MAX effect and future returns in the Chinese market after controlling for six well-known variables, namely BETA, SIZE, BM, MOM, REV, and LIQ. Further, we investigate the interaction between MAX and the mispricing concept, as well as MAX as a lottery-type solution of the IVOL puzzle in the Chinese market. These empirical findings significantly contribute to and extend the existing evidence of the MAX anomalies in the emerging stock market. Following the approach of Stambaugh et al. (2015), we develop a framework to directly study whether the observed MAX effect is consistent with the mispricing. Central to this analysis, the MIS index is devised using five significant anomalies in the Chinese stock market, including BM, NOA, GPP, ROE, and ROA. From the double-sorted MIS-MAX portfolio analysis, we determine that the MAX effect has high relevance with overpriced stocks categorized by the MIS index, which can be explained by asymmetric arbitrage. In addition, through our double-sorted IVOL-MAX and MAX-IVOL portfolio analysis, we determine that MAX cannot be a source for the IVOL effect in the Chinese stock market. This may lead the evidence that each of MAX and IVOL may have some independent information value for determining stock

prices in the Chinese stock market, unlike in the U.S. one. These findings are robust in the changes of empirical design and the sub-periods considering the events of market crash. Therefore, our study potentially makes a strong contribution to assist future studies aiming to further explore the unique relationship between MAX and IVOL in the Chinese stock market.

Appendix A: Variable definitions

Beta (BETA) is estimated following Fama and French (1992), by running a time-series regression based on the monthly return observations over the prior 60 months if available (or a minimum of 24 months).

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_i^1 (R_{m,t} - R_{f,t}) + \beta_i^2 (R_{m,t-1} - R_{f,t-1}) + \varepsilon_{i,t} \quad (3a)$$

$$BETA_i = \hat{\beta}_i^1 + \hat{\beta}_i^2 \quad (3b)$$

where the beta of stock i ($BETA_i$) is the sum of the slope coefficients on the current and lagged excess market returns.

Size (SIZE) is the natural logarithm of equity market value for a firm in June of year y and is assigned from July of year y to June of year $y + 1$.

Book to market (BM) is used as the book value of equity for fiscal year $y - 1$ and market capitalization at the end of December of year $y - 1$, and this ratio is assigned to July of year y to June of year $y + 1$.

Momentum (MOM) is the cumulative returns of stock i from months $t - 7$ through $t - 2$ to control for short-term momentum effects following Jegadeesh and Titman (1993).

Short-term reversal (REV) represents the lagged 1-month of monthly stock return to control for the return reversal effects following Huang et al. (2010).

Liquidity (LIQ) is measured by the number of shares traded divided by the number of shares outstanding of the previous 36 months, after which its natural logarithm is calculated following Chordia et al. (2001).

Price (PRICE) is the stock price at the end of the month following Bali et al. (2011).

Net operating assets (NOA) is calculated by dividing the difference between operating asset and operating debt for the fiscal year ending in calendar year $y - 1$ with the 1-yearly-lagged total asset of that fiscal year following Hirshleifer et al. (2004). This ratio is then assigned to July of year y to June of year $y + 1$.

Gross profitability premium (GPP) is calculated by dividing the difference between sale and cost of sale with total asset for the fiscal year ending in calendar year $y - 1$ following Novy-Marx (2013), and is then assigned to July of year y to June of year $y + 1$.

Return on asset (ROA) is determined as the quarterly net income divided by the 1-quarter-lagged total asset following Fama and French (2006). This ratio is assigned to the next three months.

Return on equity (ROE) is estimated as the quarterly net income divided by the 1-quarter-lagged total shareholders' equity following Liu et al. (2019). This ratio is assigned to the next three months.

Appendix B: Table

Existence of anomalies in the Chinese stock market

	LOW	2	3	4	HIGH	H-L	FF3 Alpha
Panel A: Book to market - BM							
EW	0.0089	0.0117	0.0137	0.0143	0.0143	0.0054[b] (2.09)	0.0010 (0.98)
VW	0.0032	0.0051	0.0078	0.0087	0.0096	0.0064[c] (1.85)	0.0017 (1.54)
Panel B: Gross profitability premium - GPP							
EW	0.012	0.0128	0.0137	0.0131	0.0129	0.0009 (0.52)	0.0033[b] (2.05)
VW	0.0052	0.0064	0.0085	0.0062	0.0078	0.0026 (1.03)	0.0059[a] (3.19)
Panel C: Return on assets – ROA							
EW	0.0097	0.0109	0.0119	0.0149	0.02	0.0103[a] (2.78)	0.0198[a] (6.75)
VW	0.0018	0.0048	0.0054	0.0065	0.0107	0.0089[b] (2.09)	0.0204[a] (8.57)
Panel D: Return on equity – ROE							
EW	0.0100	0.0108	0.0116	0.0146	0.0199	0.0099[a] (2.95)	0.0184[a] (4.02)
VW	0.0024	0.0042	0.0045	0.007	0.0118	0.0094[b] (2.21)	0.0203[a] (3.69)
Panel E: Net operating assets - NOA							
EW	0.0174	0.0144	0.0122	0.0109	0.0097	-0.0077[c] (-1.80)	-0.0040[b] (-2.05)
VW	0.0106	0.0105	0.0089	0.0079	0.0062	-0.0044 (-0.94)	0.0014 (1.21)
Panel F: Momentum - MOM							
EW	0.0145	0.0152	0.0155	0.0135	0.0111	-0.0034 (-0.91)	0.0048 (1.33)
VW	0.006	0.007	0.0089	0.0081	0.0051	-0.0009 (-0.21)	0.0067 (1.57)
Panel G: Accruals - ACC							
EW	0.0141	0.0144	0.0141	0.0136	0.0136	-0.0005 (-0.23)	-0.0008 (-0.47)
VW	0.0062	0.0082	0.0075	0.0079	0.0089	0.0027 (0.83)	0.0009 (0.41)
Panel H: Composite equity issues - CEI							
EW	0.0136	0.0138	0.0146	0.0151	0.0126	-0.0010[c] (-1.68)	-0.0008 (-0.52)
VW	0.0072	0.0065	0.009	0.0112	0.0064	-0.0008 (-0.30)	0.0003 (0.11)
Panel I: Asset growth – AG							
EW	0.0151	0.0146	0.0143	0.0128	0.0124	-0.0027 (-1.47)	0.0012 (0.92)
VW	0.0103	0.0082	0.0093	0.0058	0.0062	-0.0041 (-1.59)	0.0017 (1.15)

Note: The table shows results on the performance from the nine anomalies in the Chinese stock market, for generating a mispricing (MIS) index. Based on the quintile portfolio, all stocks are ranked according to each anomaly indicator: BM (Panel A), GPP (Panel B), NOA (Panel C), ROA (Panel D), ROE (Panel E), MOM (Panel F), ACC (Panel G), CEI (Panel H), and AG (Panel I). These indicators are calculated as follows: BM is the Fama-French book-to-market ratio of book value of equity to market value of equity at the end of the previous calendar year; GPP is the gross profitability premium, which is the difference between sale and cost of sale divided by the total assets in fiscal years; NOA is net operating asset, which is the difference between operating asset and operating debt divided by the lagged total assets; ROA is return on asset, which is the quarterly net income divided by the 1-quarter-lagged total assets; ROE is return on equity, which is the quarterly net income divided by the 1-quarter-lagged total shareholders' equity; MOM is the cumulative returns of stock *i* from months *t*-7 through *t*-2; ACC is total accruals, which is estimated as the change in noncash current assets minus the change in current liabilities (exclusive of debt in current liabilities and income tax payable) and minus depreciation, then divided by average total assets for the previous two fiscal years; CEI is composite equity issuance, which is the log change in market capitalization minus the log return in the previous year; AG is assets' growth, which is measured as the growth in total assets from the fiscal year ending in calendar year *y*-2 to the fiscal year ending in calendar year *y*-1. In the table, the performance over subsequent months by means of monthly roll-sampling method is separately presented as the returns of quintile portfolio, the H-L zero-cost portfolio, and the risk-adjusted return (FF3 alpha) by the FF3 model. Results are divided by EW and VW weighting schemes. The t-values in parentheses are estimated based on Newey-West (1987), and their significance is presented by 'a', 'b', and 'c' based on the significance levels of '1%', '5%', and '10%', respectively.

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