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Do extreme returns matter in emerging markets? Evidence from the Chinese stock market

Gilbert V. Nartea[a], Dongmin Kong[b], Ji Wu[c,*]

[a] Department of Finance, Waikato Management School, University of Waikato, Hamilton, New Zealand
[b] Department of Finance, Zhongnan University of Economics and Law, #182 Nanhu Ave., Wuhan 430073 PR China
[c] School of Economics and Finance, Massey Business School, Massey University – Albany Campus, Auckland, New Zealand

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ABSTRACT

Recent evidence in the U.S. and Europe indicates that stocks with high maximum daily returns in the previous month, perform poorly in the current month. We investigate the presence of a similar effect in the emerging Chinese stock markets with portfolio-level analysis and firm-level Fama–MacBeth cross-sectional regressions. We find evidence of a MAX effect similar to the U.S. and European markets. However, contrary to U.S. and European evidence, the MAX effect in China does not weaken much less reverse the anomalous idiosyncratic volatility (IV) effect. Both the MAX and IV effects appear to independently coexist in the Chinese stock markets. Interpreted together with the strong evidence of risk-seeking behaviour among Chinese investors, our results partially support the suggestion that the negative MAX effect is driven by investor preference for stocks with lottery-like features.

1. Introduction

Motivated by recent evidence from Kumar (2009) that investors in the U.S. stock markets exhibit a preference for stocks with lottery-like characteristics, Bali et al. (2011) investigate the role of extreme positive returns in the cross-sectional pricing of stocks in the U.S. Considering stocks that exhibit extreme positive returns to be lottery-like, they find that stocks with the highest maximum daily returns in the previous month (MAX), tend to perform poorly in the following month. For their decile portfolios, they report negative raw and risk-adjusted return spreads between portfolios with the highest and lowest maximum daily returns exceeding 1% per month. The negative relationship is robust even as they control for size, book-to-market, momentum, short-term reversal, liquidity, and skewness. Bali et al. (2011) also find that the MAX effect reverses the anomalous negative relationship between idiosyncratic volatility and stock returns (henceforth, the IV effect) first documented by Ang et al. (2006, 2009) in the U.S. markets, leading them to argue that MAX is the true effect and that idiosyncratic volatility is just a proxy for MAX.

Bali et al. (2011) explain the apparent negative MAX effect as a result of investor preference for stocks with lottery-like characteristics, in particular those with the potential to produce high maximum daily returns albeit with low probability. A preference for these stocks leads to overpayment which eventually results to underperformance in the following month. Such behaviour is consistent with two descriptive models of decision making under uncertainty – Tversky and Kahneman's (1992) cumulative prospect theory (CPT), as recently extended by Barberis and Huang (2008) and Kothiyal et al. (2011) and the optimal expectations framework of Brunnermeier and Parker (2005) and Brunnermeier et al. (2007). Cumulative prospect theory is a non-expected utility model that accommodates overweighting of tails of distributions as a modelling device that captures the common preference for lottery-like (positively skewed) wealth distributions (Barberis and Huang, 2008). In the optimal expectations framework of Brunnermeier and Parker (2005) and Brunnermeier et al. (2007) decision makers deliberately choose to distort their beliefs by overestimating the probabilities of events in which their investments pay off well. Brunnermeier et al. (2005) show that this model leads to a) portfolios that are underdiversified, b) investors exhibiting a preference for lottery-like assets and c) that these lottery-like assets tend to have lower returns. Fong and Toh (2014) suggest that investor optimism generates a preference for lottery-type stocks thereby providing a behavioural underpinning to the optimal expectations framework.

Empirical evidence of the MAX effect in other markets is still very sparse. While Annaert et al. (2013) and Walkshausl (2014) confirm the presence of a MAX effect in European markets and Nartea et al. (2014) and Carpenter et al. (2014) also document

* Corresponding author.
E-mail addresses: gilbert.nartea@waikato.ac.nz (G.V. Nartea), kongdm@mail.hust.edu.cn (D. Kong), georgejiwu@hotmail.com (J. Wu).

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a negative MAX effect in the South Korean and Chinese stock markets, respectively, we are not aware of other studies done in other Asian emerging stock markets. This paper investigates in more detail the presence of a MAX effect in China. The Chinese stock market is an interesting case in which to analyse the robustness of the MAX effect. First, it is a large and important market. The Chinese stock market is the world's largest emerging market and the Chinese economy is the world's second largest. China is also the world's largest investor and greatest contributor to global economic growth and its stock market arguably has a crucial role to play in sustaining this growth (Carpenter et al. 2014). Second, due to restrictions on capital flows and holdings, the Chinese stock market is unique in the sense that it is a segmented market with Chinese investors dominating ownership of stocks. Thus, this is a different analysis than looking at developed markets which are integrated or even other emerging markets which are partially integrated. By examining stock returns in the Chinese stock markets, we are effectively looking at the 'preferences' of a completely different set of investors. Third, by focussing on China we are presented with a unique opportunity to test Bali et al.'s (2011) "preference for lottery stocks" explanation of the MAX effect, in as much as Chinese investors have been shown to exhibit risk-seeking behaviour (see for example Ma, 1996; Ng and Wu, 2006; Lee and Wong, 2009; Fong et al., 2010). Studies have also shown that social gambling is considered an acceptable form of entertainment within the Chinese culture (Raylu, and Oei, 2004; Loo et al., 2008) which leads to a predisposition for lottery-like stocks. If Bali et al.'s (2011) explanation is valid, we expect to document a negative MAX effect in the Chinese stock markets.

In less than twenty-five years China's two stock markets, located in Shanghai and Shenzhen, have grown from a handful of listed stocks to collectively become the second largest stock market in the world by early 2015 behind only the US stock markets, and the largest emerging stock market. Inspite of this remarkable progress there is still enormous potential for growth since the proportion of their market capitalisation to China's GDP is about 98% as of the end of 2015 compared with 155% for the U.S. stock markets. In addition, the Chinese stock markets also lag their developed market counterparts in terms of financial sophistication and market efficiency. For instance short selling was not allowed until March 2010 when a pilot program designated 90 stocks as eligible to be sold short and/or purchased on margin. Inspite of this initiative, short-selling is still not allowed for a majority stocks traded in the Chinese stock markets. As China continues to open its markets to foreign investors, understanding the factors that drive stock price movements in its stock markets has become an important issue.

For comparability we follow Bali et al.'s (2011) portfolio sorting approach. We sort stocks according to maximum daily returns in the previous month, form portfolios on this basis and track the returns of these portfolios in the succeeding month, reforming portfolios monthly. We also vary the portfolio holding period to three and 6 months and confirm the robustness of our results with a double-sort procedure to control for various cross-sectional effects including size, book-to-market, momentum, short-term reversal, closing price, co-skewness, idiosyncratic skewness, idiosyncratic volatility, illiquidity, and market beta. In addition to portfolio analysis, we perform firm-level Fama–MacBeth cross-sectional regressions as further robustness tests.

Our results can easily be summarised. First, we find evidence of a MAX effect in China similar to the U.S., European, and Korean markets. This effect persists even if we extend the holding period to three and 6 months. Our results add to the existing evidence of a negative MAX effect in the U.S., European, and Korean stock markets and underscore the growing importance of extreme returns in asset pricing across equity markets. Interpreted together with the strong evidence of risk-seeking behaviour among Chinese investors documented in the extant literature, our results partially support Bali et al.'s (2011) suggestion that the negative MAX effect is driven by investor preference for stocks with lottery-like features. We suggest that the negative MAX effect persists due to severe short-selling constraints in the Chinese stock markets that limit arbitrageurs from trading this effect away. Second, we find that the MAX effect does not necessarily weaken the anomalous IV effect in the Chinese stock market contrary to the findings of Annaert et al. (2013) for European markets, much less reverse it as documented by Bali et al. (2011) for the U.S. markets. In fact our results suggest that both the MAX and IV effects can independently coexist in the Chinese stock markets which emphasise the importance of in-country verification of certain anomalies initially documented in developed markets.

The rest of the paper is organised as follows: Section 2 describes our data and discusses our estimation procedures. It describes the single-sort method of portfolio analysis and the double-sort procedure that is used to control for various known effects. Section 3 reports the empirical results with Section 3.1 dealing with results of portfolio-level analysis while Section 3.2 reports results of firm-level Fama–MacBeth cross-sectional regressions. We extend the portfolio holding period to three and 6 months in Section 3.3. Section 4 concludes the paper.

2. Data and methods

Daily and monthly stock returns and accounting data for individual firms were obtained from CSMAR. We use A-shares listed in both the Shanghai and Shenzhen stock exchanges.[1] The data set covered the period from January 1997 with 515 firms, to December 2014 with 2353 firms with an average of 1383 firms per month resulting in a total of 298,710, firm-month observations. The risk-free rate which is defined as the demand deposit rate was also obtained from CSMAR. Market returns are the value-weighted returns of all firms used in the study.

Following common practice in the existing literature we eliminated investment trusts, closed-end funds, exchange traded funds, and preferred shares from the sample. We also deleted stocks with monthly returns greater than 200% to avoid the influence of extreme returns and possible data recording errors. We retained delisted stocks to avoid any biases that may be caused by their deletion from the data set.[2] To mitigate the effect of outliers we ignored daily returns on the first trading day for IPO firms and deleted daily returns larger than 10% or smaller than −10% (the daily price limit in the Chinese stock market).[3]

The Chinese stock market is subject to trading price limits which were introduced by the China Securities Regulatory Commission to reduce stock market volatility and protect retail in-

[1] Our sample excludes B- and H-shares. A-shares were introduced in the early 1990s and are traded in the main board of the Shanghai and Shenzhen stock exchanges. B-shares, introduced in 1992, can only be traded by foreign investors (mainly institutional investors) until 2002. B-shares are denominated in U.S. or Hong Kong dollars depending whether they are traded on the Shanghai or Shenzhen stock exchanges. More importantly, B-shares apply a different accounting standard compared to A-shares. H-shares are Chinese companies listed in the Hong Kong stock exchange from 1993. These are mainly leading corporations in China.

[2] In results not reported here, we examined the number of delisted stocks every year from 1997 to 2014. Results show that the number of delisted stocks is very small at around 5.1 stocks per year. Results are available upon request.

[3] Although the price limit is 10% in China's stock markets, the actual range of price change in the trading is not exactly [-10%, +10%]. For example, if the close price of day t is RMB 12.35, the effective price in day t-1 is [12.35 – 12.35*10%, 12.35+12.35*10%], i.e., [11.115, 13.585]. Since the smallest bid-ask spread is 0.01, therefore the actual price range is [11.12, 13.59] with actual range of price change over [-9.96%, +10.04%]. In our empirical implementation, we use the actual price range.

vestors. These limits only allow stock prices to move up or down on a single trading day by a maximum of 10% from the last closing price. The policy artificially makes a barrier for the stock price to efficiently reflect any news impacting stocks, limiting the efficiency of the Chinese stock market. To account for this restriction we follow the approach taken in the literature on futures contracts that are also subject to similar price move limits. We aggregate over daily returns to get a proxy for the true daily return in the absence of price limits. For example, for a stock with a successive daily return of 10% (hitting the limit) and 5%, the assumption is that the initial daily return would have been 15% in the absence of the restriction. Similarly, a daily return sequence of 10%, 10%, and 5% would be aggregated to 25%.[4]

At the beginning of each month, we form quintile portfolios according to MAX, defined as the maximum daily return in the past calendar month. We apply holding periods of one, three and 6 months and determine the raw and risk-adjusted returns (alpha) of each portfolio. Portfolios are reformed every month. The risk-adjusted return refers to the Fama–French (1993) three-factor model alpha (FF-3 alpha) estimated using the full sample of the time-series of value- or equal-weighted returns for each portfolio. We relate MAX in month t with raw and risk-adjusted returns in month $t+1$, the three-month return ending in month $t+3$, and the 6-month return ending in month $t+6$.

We control for several variables including size, book-to-market (BM), intermediate-term momentum, short-term reversal, closing price, co-skewness, idiosyncratic skewness, idiosyncratic volatility, illiquidity, and market beta using dependent 3×5 bi-variate sorts similar to that employed by Bali et al. (2011). First we sort on the control factor (i.e., size, BM, momentum, and so on) into tertiles. Within each tertile we sort further into quintiles based on MAX. Then we average within each MAX category resulting in five portfolios with variation in MAX but similar levels in the control variable. For example, to control for size, stocks are first sorted into tertiles according to market capitalisation – Big, Medium, and Small. Within each size category, stocks are sorted again according to MAX into quintiles. Therefore, fifteen size-MAX portfolios are formed. To control for size, we construct a size-neutral portfolio by averaging the alphas within each MAX category. To illustrate, a size-neutral High MAX portfolio is constructed by averaging the alphas of the three High MAX portfolios, i.e., BIG-HMAX, MED-HMAX, and SMALL-HMAX, so that we have a high MAX portfolio which contains all sizes. We do the same for the other four MAX categories. This process results in five portfolios with variation in MAX but similar levels in the control variable – size. We replicate this procedure for the other control variables.

The size variable at the beginning of month t is defined as the log of the stock's market capitalization at the end of month t-1, BM is the stock's book-to-market ratio 6 months prior, i.e. at the end of t-6.[5] Following Jegadeesh and Titman (1993), the momentum variable at time t is the stock's 11-month past return lagged one month, i.e. return from month t-12 to month t-2. The short-term reversal variable is defined following Jegadeesh (1990) as the stock's one month past return, i.e. return in month t-1. Closing price is the stock's final trading price at the end of month t-1.

We follow Harvey and Siddique (2000) to decompose total skewness into idiosyncratic and systematic components by estimating the following regression for each stock within each year:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i RMRF + \gamma_i RMRF^2 + \varepsilon_{i,t}$$

where $R_{i,\,t}$ is the return on stock i on day d, $RMRF$ is the daily market return minus daily risk-free rate, $r_{f,\,t}$ is the risk-free rate on day d, and $\varepsilon_{i,\,t}$ is the idiosyncratic return on day d.

The idiosyncratic skewness (ISKEW) of stock i in month t is defined as the skewness of daily residuals $\varepsilon_{i,\,t}$ in month t. The systematic skewness (SSKEW) or co-skewness of stock i in month t is the estimated slope coefficient $\hat{\gamma}_i$.

To construct the illiquidity proxy, we follow Amihud (2002) to define illiquidity as:

$$\frac{1}{\mathrm{Day}_{\mathrm{i,m}}} \sum_{t=1}^{Day_{i,m}} \frac{|Ret_{i,t}|}{Vol_{i,t}}$$

where $Day_{i,m}$ is the number of days for which data are available for stock i in month m, $Ret_{i,t}$ is the return on stock i on day t of month m and $Vol_{i,t}$ is the respective daily trading volume in dollars. The idiosyncratic volatility (IV) of stock i at the beginning of month t is defined as the standard deviation of daily residuals from the Fama–French three factor model (1) estimated using daily returns in month t-1. $R_{i,t}$ and MKT are excess returns of stock i and the market, respectively, over the risk-free rate. We follow Fama and French (1993) in constructing SMB and HMLin the three-factor model.[6]

$$R_{i,t} = \alpha + \beta_{MKT,i,m} MKT_t + \beta_{SMB,i,m} SMB_t + \beta_{HML,i,m} HML_t + \varepsilon_{i,t} \quad (1)$$

Market beta is computed following Carpenter et al. (2014) and is obtained from regressing daily firm return on daily current, lead, and lagged market returns over the previous month and summing the three coefficients.

3. Empirical results

3.1. Portfolio analysis

3.1.1. Univariate sorting

Table 1 shows the returns and FF-3 alpha of portfolios sorted on the maximum daily returns in the past month (MAX). We report results for both value- and equal-weighted portfolios. Value-weighted returns are weighted by the market value of total shares in a particular portfolio. Columns 1 and 3 indicate the presence of a negative MAX effect in both equal- (EW) and value-weighted (VW) raw returns. Columns 2 and 4 also indicate the presence of a negative MAX effect in both EW and VW FF-3 alphas. Our EW (VW) return and alpha spreads are higher (lower) than those documented by Bali et al. (2011) for the U.S. markets but our numbers are generally lower than those documented by Nartea et al. (2014) for the Korean stock market.

Table 2 presents the characteristics of the MAX-sorted portfolios. Table 2 indicates that high MAX stocks tend to be smaller, have lower BM, are winners in the previous 11 months as well as in the previous month, are higher priced, more liquid, have more positively skewed return distributions, have higher IV, and higher market beta than low MAX stocks. The last three characteristics are consistent with high MAX stocks exhibiting lottery-like features. More importantly, most of these characteristics of high MAX stocks point toward lower returns in the succeeding month based on

[4] We thank an anonymous reviewer for suggesting this adjustment. In results not reported here, we find that the ratio of the price hitting the 10% price limit is low with a mean value of 0.77% which means that for a specific stock, there are only 2 days (0.77%*250 = 1.92) where it hits the price limit in a typical year with 250 trading days. Results are available upon request. In addition, in an earlier version of this paper we also find a significant MAX effect even if we do not control for price trading limits.

[5] Clubb and Naffi (2007) also show that expected book-to-market ratios also explain UK stock returns. However, in this study we only deal with past book-to-market ratios. Michou (2009) also reports that the predictive power of the book-to-market spread depends on portfolio formation strategies and the relative proportion of large-caps, small-caps, value, and growth stocks in the portfolio.

[6] A description on how to construct Fama-French three-factor model in the China stock markets, and the correlation of three factors is presented in Appendix A.

Table 1
Returns on portfolios sorted by MAX.
At the beginning of every month we sort stocks into quintiles according to their maximum daily return (MAX) in the past calendar month. We compute each portfolio's equal- and value-weighted raw returns for the current month. We also estimate each portfolio's alpha (α coefficient) from the FF3-factor model estimated using the full sample of monthly value- or equal-weighted returns for each portfolio. The last row shows the difference in monthly returns and differences in alpha between the high and low MAX portfolios. Newey–West *t-statistics* are reported in parenthesis. We conduct the analysis for the full sample period 1997:01–2014:12.

Quintile	EW portfolios		VW portfolios	
	Average return	FF-3 alpha	Average return	FF-3 alpha
Low MAX	0.0183	0.0029	0.0134	0.0024
	(2.7038)	(2.0038)	(2.2247)	(1.6527)
2	0.0188	0.0027	0.0142	0.0023
	(2.7560)	(2.1922)	(2.2098)	(2.1737)
3	0.0175	0.0014	0.0147	0.0028
	(2.5710)	(1.2539)	(2.2566)	(2.6960)
4	0.0133	−0.0026	0.0108	−0.0005
	(1.9814)	(−2.3393)	(1.6348)	(−0.3907)
High MAX	0.0072	−0.0085	0.0074	−0.0045
	(1.0460)	(−5.7272)	(1.0639)	(−2.4807)
High-Low	−0.0111	−0.0114	−0.0060	−0.0070
	(−6.2111)	(−6.2647)	(−2.3014)	(−2.5686)

the BM effect, short-term reversal effect (Jegadeesh, 1990; Lehman, 1990), negative IV effect (Ang et al., 2006, 2009), investor preference for positive skewness (Golec and Tamarkin, 1998; Mitton and Vorkink, 2007), and the liquidity effect. Therefore, these variables could potentially explain the negative MAX effect. We test this formally using dependent bivariate sorts and cross-sectional regressions and report the results in later sections.

3.1.2. Bivariate sorting

In this section we control for size, BM, momentum, short-term reversal, closing price, co-skewness, idiosyncratic skewness, IV, illiquidity, and market beta to test the robustness of the apparent negative MAX effect using a battery of 3×5 bivariate sorts and report the results in Table 3. Following Bali et al. (2011) we focus our attention on the alphas since they control for the standard set of systematic factors.

Our results show that 16 out of 20 *t-statistics* reported in Table 3 for the average *HMAX-LMAX* alpha spreads are all highly significant (absolute value greater than 3). Given that the sample period is short and returns are volatile, we interpret this as evidence supporting the existence of a MAX effect in China when we hold portfolios for1-month.

3.2. Firm-level cross-sectional regressions

Since dependent bi-variate sorts cannot be used to control for multiple effects simultaneously we also conduct firm-level Fama–MacBeth regressions. In addition, the portfolio analysis conducted earlier loses too much information through aggregation so we estimate the following model and its nested versions:

$$\begin{aligned} R_{i,t} = {} & \beta_{0,t-1} + \beta_{1,t-1}MAX_{i,t-1} + \beta_{2,t-1}SIZE_{i,t-1} + \beta_{3,t-1}BM_{i,t-1} \\ & + \beta_{4,t-1}MOM_{i,t-1} + \beta_{5,t-1}REV_{i,t-1} + \beta_{6,t-1}CP_{i,t-1} \\ & + \beta_{7,t-1}SSKEW_{i,t-1} + \beta_{8,t-1}ISKEW_{i,t-1} + \beta_{9t-1}IV_{i,t-1} \\ & + \beta_{10,t-1}ILLIQ_{i,t-1} + \beta_{11,t-1}BETA_{i,t-1} + \varepsilon_{i,t-1} \end{aligned} \tag{2}$$

Realised stock return in month *t*, $R_{i,t}$, is regressed on 1-month lagged values of the maximum daily return in the previous month (*MAX*), log of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*MOM*), short-term reversal (*REV*), closing price (*CP*), co-skewness (*SSKEW*), idiosyncratic skewness (*ISKEW*), realized idiosyncratic volatility (*IV*), Amihud (2002) illiquidity *(ILLIQ)*, and market beta (*BETA*). The variables are as defined earlier. Table 4 reports the time series averages of the slope coefficients over the 216 months from 1997:01–2014:12 for univariate regressions. The Newey–West *t-statistics* are given in parenthesis. The univariate regression shows a statistically significant negative relation between *MAX* and the cross-section of 1-month ahead stock returns. The results also show significant negative coefficients for *REV, ISKEW, IV,* and a significant positive coefficient for *BM* and *ILLIQ* consistent with expectations. The rest of the coefficients are not statistically significant.

The regressors are winsorized (1% and 99%) to mitigate the problems caused by outliers. We employ a two-stage Fama–Macbeth regression. In the first stage, we perform monthly regressions. To alleviate the heteroscedasticity problem, generalised least squares (GLS) are used in the second stage of the Fama–Macbeth regression. In the GLS estimation, the time periods with more observations have greater influence on the coefficient estimates. In particular, we weight a given time period's coefficient by the number of observations in that time period versus the total observations in the regression.[7]

[7] One concern is that highly correlated regressors may cause multicollinearity issues, which according to the results in Ahn and Horenstein (2013) may lead to seriously biased estimates. To check for multicollinearity, we compute the variance inflation factor (VIF), and find that the mean VIF is 1.56 (far less than the threshold value of 10) and the condition number value of all independent variables is 3.223 (far less than the threshold value of 15), which indicate that the multicollinearity is less likely to be a serious problem in our empirical analysis. In addition, we find

Table 2
Characteristics of portfolios sorted by MAX.
At the beginning of every month we sort stocks into quintiles according to their maximum daily return in the past calendar month (MAX). The table reports for each quintile, the monthly averages of various characteristics of the MAX-sorted portfolios over the period 1997:01–2014:12. Size at the end of month *t* is defined as the log of the firm's market capitalization at the end of month *t*; BM is the firm's book-to-market ratio 6 months prior, i.e. at the end of *t-6*. Following Jegadeesh and Titman (1993), Momentum at time *t* is the stock's 11-month past return lagged one month, i.e. return from month *t-12* to month *t-2*. REV in month *t* is short-term reversal defined as the return on the stock in month *t-1*, following Jegadeesh (1990) and Lehmann (1990). CP is the closing price for stocks in the end of previous month. SSKEW refers to co-skewness of stock *i* in month *t*, and according to Harvey and Siddique (2000). ISKEW is calculated using the residuals from the market model regression used to construct SSKEW. IV is the standard deviation of the residuals of the FF3-factor model, using daily data for the previous 22 trading days. ILLIQ is Amihud (2002) illiquidity ratio; Market beta is computed following Carpenter et al. (2014) and is obtained from regressing daily firm return on daily current, lead, and lagged market returns over the previous month and summing the three coefficients. The last row is the difference between the high and low MAX portfolios. *T-statistics* are reported in parenthesis.

	Size	BM	Momentum	REV	CP	SSKEW	ISKEW	IV	ILLIQ	BETA
Low MAX	14.3130	0.4433	0.1804	−0.0321	10.0417	−1.5173	0.1174	0.0121	0.0026	0.9370
2	14.2111	0.4277	0.2023	−0.0131	10.0749	−1.8750	0.2482	0.0143	0.0028	0.9831
3	14.2051	0.4120	0.2351	0.0045	10.4944	−1.8536	0.3809	0.0165	0.0027	1.0033
4	14.2246	0.4015	0.2662	0.0295	10.9765	−1.7788	0.5891	0.0194	0.0025	1.0156
High MAX	14.1747	0.3909	0.2841	0.0790	11.1925	−1.9611	0.9253	0.0253	0.0025	1.0395
High-Low	−0.1383	−0.0524	0.1037	0.1110	1.1508	−0.4438	0.8079	0.0132	−0.0002	0.1025
	(−19.3063)	(−38.9412)	(27.7684)	(113.1938)	(32.9735)	(−12.9813)	(155.4633)	(269.6941)	(−6.2729)	(58.6066)

Table 3
Alpha of double-sorted portfolios.
At the end of each month over 1997:01–2014:12, stocks are double-sorted 3 × 5, first by the control factor (Size, BM, Momentum, Rev, CP, SSKEW, ISKEW, IV, ILLIQ, and Beta) and then again by their maximum daily return in the past calendar month (MAX). The alpha of each portfolio is presented with Newey–West *t-statistics* in parenthesis. Alpha refers to the FF3-factor model alpha using the full sample of monthly returns for each portfolio. To control for a particular factor, we average the alpha within each MAX category ending up with five portfolios with dispersion in MAX but containing all values of the factor being controlled. Size, BM, Momentum, Rev, CP, SSKEW, ISKEW, IV, ILLIQ, and Beta are as defined in Table 2. *LMAX*, 2, 3, 4, and *HMAX* refer to low MAX to high MAX portfolios, respectively. To save space, we only report results of average difference between HMAX-LMAX. The full results are available upon request.

	Equal-weighted						Value-weighted					
	LMAX	2	3	4	HMAX	HMAX-LMAX	LMAX	2	3	4	HMAX	HMAX-LMAX
Panel A. Double sort on Size and MAX												
AVE	0.0031	0.0035	0.0007	−0.0013	−0.0102	−0.0133	0.0031	0.0037	0.0010	−0.0008	−0.0088	−0.0120
	(2.0989)	(2.4813)	(0.5309)	(−0.9698)	(−6.0129)	(−7.1788)	(2.2486)	(2.8084)	(0.8790)	(−0.6696)	(−5.1208)	(−6.0866)
Panel B. Double sort on BM ratio and MAX												
AVE	0.0046	0.0043	0.0010	−0.0023	−0.0114	−0.0160	0.0053	0.0040	0.0030	−0.0001	−0.0072	−0.0124
	(3.2259)	(3.0685)	(0.8179)	(−1.8328)	(−6.6018)	(−8.3436)	(3.3104)	(2.8865)	(2.5594)	(−0.0611)	(−3.4266)	(−4.9168)
Panel C. Double sort on Momentum and MAX												
AVE	0.0032	0.0031	−0.0003	−0.0015	−0.0096	−0.0129	0.0026	0.0019	0.0002	0.0001	−0.0070	−0.0096
	(2.0651)	(2.3168)	(−0.2605)	(−1.0033)	(−5.5397)	(−6.6087)	(1.6716)	(1.4278)	(0.1399)	(0.0824)	(−3.4662)	(−3.9321)
Panel D. Double sort on Rev and MAX												
AVE	0.0047	0.0045	0.0012	−0.0019	−0.0091	−0.0139	0.0040	0.0040	0.0021	−0.0003	−0.0054	−0.0094
	(3.0950)	(3.3396)	(0.9721)	(−1.5825)	(−5.2511)	(−6.4598)	(2.4411)	(2.7386)	(1.5469)	(−0.2132)	(−2.7340)	(−3.5577)
Panel E. Double sort on CP and MAX												
AVE	0.0027	0.0037	0.0001	−0.0017	−0.0098	−0.0125	0.0031	0.0027	0.0016	0.0002	−0.0062	−0.0093
	(1.8476)	(2.7408)	(0.0908)	(−1.3117)	(−5.9618)	(−6.8675)	(1.9824)	(2.0514)	(1.2502)	(0.1322)	(−3.0567)	(−3.6368)
Panel F. Double sort on SSKEW and MAX												
AVE	0.0041	0.0037	0.0005	−0.0024	−0.0094	−0.0135	0.0019	0.0007	−0.0002	−0.0022	−0.0076	−0.0095
	(2.3013)	(2.7322)	(0.4290)	(−1.9996)	(−5.1995)	(−6.3926)	(1.0477)	(0.5186)	(−0.1470)	(−1.7450)	(−3.6708)	(−3.9508)
Panel G. Double sort on ISKEW and MAX												
AVE	0.0026	0.0029	0.0008	−0.0018	−0.0079	−0.0105	0.0026	0.0021	0.0023	0.0009	−0.0023	−0.0048
	(1.6012)	(2.1073)	(0.5436)	(−1.2619)	(−4.0307)	(−4.2871)	(1.5958)	(1.6315)	(1.6507)	(0.5467)	(−0.8638)	(−1.4907)
Panel H. Double sort on IV and MAX												
AVE	−0.0008	0.0027	−0.0001	−0.0003	−0.0036	−0.0028	−0.0017	0.0011	−0.0005	0.0001	−0.0030	−0.0013
	(−0.3909)	(1.7032)	(−0.0565)	(−0.2164)	(−1.3878)	(−0.9186)	(−0.7625)	(0.6870)	(−0.3586)	(0.0814)	(−1.1091)	(−0.3667)
Panel I. Double sort on ILLIQ and MAX												
AVE	0.0030	0.0036	−0.0003	−0.0013	−0.0096	−0.0126	0.0032	0.0048	0.0021	0.0010	−0.0064	−0.0096
	(2.0289)	(2.5772)	(−0.1990)	(−0.9990)	(−5.6233)	(−6.8502)	(2.2062)	(3.3835)	(1.5908)	(0.7650)	(−3.4909)	(−4.3340)
Panel J. Double sort on BETA and MAX												
AVE	0.0029	0.0030	0.0002	−0.0013	−0.0094	−0.0124	0.0018	0.0016	0.0004	−0.0001	−0.0060	−0.0077
	(1.8906)	(2.2415)	(0.1484)	(−0.8435)	(−5.4812)	(−5.8667)	(1.0258)	(1.2043)	(0.3136)	(−0.0435)	(−2.8043)	(−2.8089)

Table 4
Univariate Fama–MacBeth regression results.
Each month from 1997:01 to 2014:12 we run a firm-level univariate Fama–MacBeth cross-sectional regression of the return on that month with 1-month lagged values of the MAX and other control variables. We report the time-series averages of the slope coefficients and their associated Newey–West *t-statistics* in a single row, but each variable is independently regressed on stock returns. MAX and the other control variables are defined in Table 2. The symbol** and *** indicates statistical significance at the 5%, and 1% level, respectively.

MAX	*Size*	*BM*	*Momentum*	*Rev*	*CP*	*SSKEW*	*ISKEW*	*IV*	*ILLIQ*	*BETA*
−0.155***	−0.002	0.012**	0.000	−0.049***	−0.000	0.001	−0.004***	−0.948***	10.068**	−0.003
(−7.209)	(−1.367)	(2.329)	(0.062)	(−4.637)	(−1.189)	(1.957)	(−4.027)	(−9.220)	(2.010)	(−0.579)

The result of the bivariate and multivariate regressions with *MAX* reported in Table 5 shows that the MAX effect survives when we control for the variables individually except when paired with IV. More importantly, the MAX effect survives even when we control for all ten variables simultaneously.

Overall the results suggest that there is evidence of a MAX effect in China in 1-month holding period returns. This finding is consistent with recent results reported in Carpenter et al. (2014) who also find evidence of a MAX effect in China.

3.3. Extended holding periods

Next we investigate the presence of the MAX effect for extended holding periods of three and 6 months. To increase the power of our tests, we follow Jegadeesh and Titman (1993) to construct portfolios with overlapping holding periods. Specifically, in any given month t, we form quintile portfolios according to MAX, defined as the maximum daily return in the past calendar month. Notably, the different holding period portfolios can therefore contain different sets of stocks. We then buy the highest MAX portfolio and sell the lowest MAX portfolio, holding this position for three or 6 months.

that our results are highly consistent regardless of the estimation method (GLS or OLS).

Table 5
Bivariate and multi-variate Fama–MacBeth regression results with MAX.
Each month from 1997:01 to 2014:12 we run a firm-level bi-variate and multi-variate Fama–MacBeth cross-sectional regression of the return on that month with 1-month lagged values of the MAX and other control variables. Each row reports the time-series averages of the slope coefficients and their associated Newey–West *t-statistics*. MAX and the other control variables are defined in Table 2. The symbol *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

MAX	*Size*	*BM*	*Momentum*	*Rev*	*CP*	*SSKEW*	*ISKEW*	*IV*	*ILLIQ*	*BETA*
−0.161***	−0.003									
(−8.418)	(−1.515)									
−0.157***		0.010*								
(−8.339)		(1.954)								
−0.151***			0.000							
(−7.696)			(0.083)							
−0.145***				-0.022*						
(−5.755)				(−1.676)						
−0.161***					−0.000					
(−8.166)					(−0.999)					
−0.158***						0.001**				
(−8.007)						(1.975)				
−0.130***							−0.002*			
(−5.496)							(−1.754)			
0.004								−0.998***		
(0.118)								(−5.996)		
−0.149***									9.561*	
(−7.022)									(1.959)	
−0.155***										0.001
(−7.103)										(0.184)
−0.072***	−0.001	0.011***	0.004	−0.042***	−0.000	0.002***	−0.002***	−0.182***	12.985***	0.001
(−3.715)	(−0.427)	(3.088)	(1.169)	(−4.620)	(−1.094)	(3.717)	(−3.404)	(−3.067)	(4.719)	(0.217)

Table 6
Returns on portfolios sorted by MAX, 6-month holding period.
At the beginning of every month we sort stocks into quintiles according to their maximum daily return in the past calendar month (MAX). We compute each portfolio's equal- and value-weighted raw returns for a 6-month holding period. We also estimate each portfolio's alpha (α coefficient) from the FF3-factor model estimated using the full sample of value- or equal-weighted returns for each portfolio. The last row shows the difference in monthly returns and differences in alpha between the high and low MAX portfolios. Newey–West *t-statistics* are reported in parenthesis. We conduct the analysis for the full sample period 1997:01–2014:12.

Quintile	EW portfolios		VW portfolios	
	Average return	FF-3 alpha	Average return	FF-3 alpha
Low MAX	0.0160	0.0020	0.0122	0.0028
	(2.3639)	(1.7444)	(1.9789)	(3.2533)
2	0.0152	0.0004	0.0119	0.0018
	(2.2280)	(0.3861)	(1.8709)	(2.1565)
3	0.0147	−0.0002	0.0111	0.0008
	(2.1503)	(−0.1767)	(1.7314)	(0.8645)
4	0.0133	−0.0015	0.0097	−0.0005
	(1.9555)	(−1.3171)	(1.5159)	(−0.4549)
High MAX	0.0102	−0.0048	0.0069	−0.0040
	(1.4884)	(−3.7113)	(1.0587)	(−3.1417)
High-Low	−0.0058	−0.0067	−0.0052	−0.0068
	(−4.7173)	(−5.8531)	(−2.9261)	(−4.4308)

Our results for the three- and 6-month holding periods are similar so to save space we only report the results for the 6-month holding period.[8]

Table 6 shows the 6-month returns and FF-3 alpha of portfolios sorted on the maximum daily returns in the past month (MAX). Table 6 shows patterns similar to the results with a 1-month holding period. Both EW and VW raw return spreads are negative and highly significant. Both EW and VW alpha spreads are also negative and highly significant. This suggests at least a 6-month lag in the adjustment of prices back to fundamental levels.

All the average *HMAX-LMAX* alpha spreads reported in Table 7 remain significantly negative even when we control for the various effects with bivariate portfolio sorts, except when we control for IV.

The results become more interesting when we employ firm-level Fama–MacBeth cross-sectional regressions. The results of univariate regressions reported in Table 8 show a significantly negative MAX effect. We also observe significant size, BM, reversal, skewness, and illiquidity effects with expected signs. Interestingly we also observe a highly significant anomalous negative IV effect consistent with the findings of Nartea et al. (2013).

In Table 9, we report the results when we control for various effects individually with firm-level bivariate regressions. Table 9 shows that the MAX effect remains significantly negative in bivariate regressions. More importantly, the negative MAX effect remains significant even when we control for all ten variables simultaneously. It is equally interesting to note that the negative IV effect survives in a multivariate setting that includes MAX. This indicates that both MAX and IV effects appear to coexist in China and does not support the suggestion of Bali et al. (2011) that MAX is the true effect for which idiosyncratic volatility is only a proxy.

Finally, as the number of firms in our sample grows dramatically from 515 in 1997 to 2353 in 2014, we split the sample into two periods. The sub-period results reported in Table 10 show that our results are stronger from 2005 to 2014. Though the coefficient of MAX is negative in the period from 1997 to 2004, it is not significant. Further, when split into size groups, the results reported in Table 10 indicates that the MAX effect is more pronounced in big firms. This suggests that investor preference for high MAX stocks in China is more evident for big firms possibly because these are cheaper stocks. There is anecdotal evidence that big firms in China are low-priced stocks. For example, the average market capitalization of the 30 most expensive stocks in the Chinese stock markets is about RMB10 billion, compared RMB100 billion for the 30 cheapest stocks. In results not reported here we also find that the average closing price of our largest size quintile is significantly lower than that of the smallest size quintile.[9]

[8] Results for the three-month holding period are available upon request.

[9] These results are available from the authors upon request.

Table 7
Alpha of double sorted portfolios, 6-month holding period.
At the end of each month over 1997:01–2014:12, stocks are double-sorted 3 × 5, first by the control factor (Size, BM, Momentum, Rev, CP, SSKEW, ISKEW, IV, ILLIQ, and Beta) and then again by their maximum daily return in the past calendar month (MAX). The alpha of each portfolio is presented with Newey–West *t-statistics* in parenthesis. Alpha refers to the FF3-factor model alpha using the full sample of monthly returns for each portfolio. To control for a particular factor, we average the alpha within each MAX category ending up with five portfolios with dispersion in MAX but containing all values of the factor being controlled. Size, BM, Momentum, Rev, CP, SSKEW, ISKEW, IV, ILLIQ, and Beta are as defined in Table 2. *LMAX*, 2, 3, 4, and *HMAX* refer to low MAX to high MAX portfolios, respectively. To save space, we only report results of average difference between HMAX-LMAX. The full results are available upon request.

	Equal-weighted						Value-weighted					
	LMAX	2	3	4	HMAX	HMAX-LMAX	LMAX	2	3	4	HMAX	HMAX-LMAX
Panel A. Double sort on size and MAX												
AVE	0.0024	0.0007	0.0005	−0.0001	−0.0038	−0.0062	0.0026	0.0012	0.0007	0.0002	−0.0035	−0.0061
	(2.0770)	(0.5976)	(0.4017)	(−0.1008)	(−3.0503)	(−5.8496)	(2.3890)	(1.0995)	(0.6908)	(0.1566)	(−2.9204)	(−5.4311)
Panel B. Double sort on BM ratio and MAX												
AVE	0.0031	0.0012	0.0003	−0.0008	−0.0050	−0.0081	0.0044	0.0027	0.0017	0.0006	−0.0040	−0.0084
	(2.5105)	(1.0181)	(0.3176)	(−0.7257)	(−3.8449)	(−7.4125)	(3.7844)	(2.4594)	(1.6512)	(0.4969)	(−2.9533)	(−5.5710)
Panel C. Double sort on Momentum and MAX												
AVE	0.0021	0.0008	0.0004	−0.0003	−0.0038	−0.0059	0.0024	0.0009	0.0005	0.0002	−0.0036	−0.0060
	(1.7873)	(0.6546)	(0.3681)	(−0.2448)	(−3.0495)	(−5.7095)	(2.0438)	(0.8696)	(0.4542)	(0.1501)	(−2.7595)	(−4.3201)
Panel D. Double sort on Rev and MAX												
AVE	0.0035	0.0011	0.0008	−0.0004	−0.0040	−0.0075	0.0033	0.0016	0.0014	0.0006	−0.0032	−0.0065
	(2.9988)	(0.9434)	(0.7729)	(−0.3654)	(−3.0084)	(−6.1131)	(3.0293)	(1.4548)	(1.3488)	(0.5190)	(−2.2740)	(−4.2229)
Panel E. Double sort on CP and MAX												
AVE	0.0022	0.0008	0.0006	−0.0003	−0.0039	−0.0061	0.0025	0.0012	0.0009	−0.0001	−0.0037	−0.0062
	(1.8722)	(0.7026)	(0.5637)	(−0.2414)	(−3.1897)	(−6.1629)	(2.1602)	(1.1861)	(0.8620)	(−0.0489)	(−2.9534)	(−4.7573)
Panel F. Double sort on SSKEW and MAX												
AVE	0.0021	0.0008	0.0005	−0.0004	−0.0039	−0.0059	0.0014	0.0006	0.0002	−0.0005	−0.0043	−0.0057
	(1.6586)	(0.7062)	(0.4181)	(−0.3387)	(−3.0551)	(−5.3851)	(1.1372)	(0.4702)	(0.1647)	(−0.4056)	(−3.1554)	(−4.0104)
Panel G. Double sort on ISKEW and MAX												
AVE	0.0018	0.0007	0.0005	−0.0006	−0.0034	−0.0052	0.0022	0.0016	0.0013	0.0005	−0.0023	−0.0045
	(1.3765)	(0.5393)	(0.4431)	(−0.5092)	(−2.5084)	(−3.7964)	(1.8216)	(1.4792)	(1.2572)	(0.4602)	(−1.5594)	(−2.5502)
Panel H. Double sort on IV and MAX												
AVE	0.0038	0.0022	0.0025	0.0020	0.0020	−0.0018	0.0021	0.0023	0.0028	0.0019	0.0015	−0.0006
	(2.3426)	(1.6315)	(1.6470)	(1.1225)	(1.1162)	(−0.8351)	(1.3729)	(1.7492)	(2.0743)	(1.1939)	(0.8485)	(−0.2475)
Panel I. Double sort on ILLIQ and MAX												
AVE	0.0021	0.0007	0.0005	0.0000	−0.0037	−0.0058	0.0019	0.0013	0.0011	0.0010	−0.0029	−0.0048
	(1.6847)	(0.6103)	(0.3850)	(−0.0147)	(−3.0204)	(−5.5081)	(1.6036)	(1.1019)	(0.9967)	(0.9001)	(−2.4207)	(−4.1108)
Panel J. Double sort on BETA and MAX												
AVE	0.0018	0.0003	0.0001	−0.0005	−0.0040	−0.0058	0.0011	0.0002	−0.0001	−0.0002	−0.0035	−0.0046
	(1.4514)	(0.2693)	(0.0478)	(−0.4447)	(−3.2155)	(−5.2255)	(0.8419)	(0.1795)	(−0.0665)	(−0.1363)	(−2.5938)	(−3.3422)

Table 8
Univariate Fama–MacBeth regression results, 6-month holding period.
Each month from 1997:01 to 2014:12 we run a firm-level univariate Fama–MacBeth cross-sectional regression of the 6-month return ($t+1$ to $t+6$) with 1-month lagged values (t) of the MAX and other control variables. We report the time-series averages of the slope coefficients and their associated Newey–West *t-statistics* on a single row, but each variable is independently regressed on stock returns. MAX and the other control variables are defined in Table 2. The symbol *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

MAX	*Size*	*BM*	*Momentum*	*Rev*	*CP*	*SSKEW*	*ISKEW*	*IV*	*ILLIQ*	*BETA*
−0.581***	−0.020**	0.049**	-0.013	−-0.100***	−0.002	0.001	−0.008***	−2.539***	60.299***	−0.002
(−8.005)	(−2.556)	(2.470)	(−0.430)	(−3.167)	(−1.503)	(0.224)	(−4.269)	(−7.115)	(4.085)	(−0.123)

Our results suggest that the negative MAX effect could last as long as 6 months. It is interesting to note that both MAX and IV effects survive in a multivariate setting. So at worst, these two effects appear to be independent of each other in the Chinese stock markets contrary to the suggestion of Bali et al. (2011) that idiosyncratic volatility effect could just be proxying for the MAX effect.

Overall, we find evidence of a negative MAX effect in the Chinese stock markets for all three holding periods. We suggest that the persistence of the negative MAX effect stems from constraints to short-selling in the Chinese stock markets which limit the opportunity for arbitrage.

Our results are consistent with a market driven by investors with a preference for stocks that have exhibited extreme positive returns in the past month. To the extent that such stocks exhibit lottery-like features, our results partially support the suggestion of Bali et al. (2011) that investor preference for lottery-like stocks drive the apparent negative MAX effect. In China however, this preference for high MAX stocks tend to be more pronounced among large stocks presumably because these are generally low-priced stocks. Indeed apart from anecdotal evidence, there is a body of literature that suggests risk-seeking behaviour among Chinese investors. Ng and Wu (2006) report that Chinese investors tend to prefer stocks with large betas and high idiosyncratic risk based on a comprehensive analysis of 64.22 million trades of 6.8 million institutional and individual investors in mainland China. Lee and Wong (2009) also suggest that Chinese investors tend to trade more heavily on riskier stocks based on an analysis of panel data drawn from the Shanghai stock market. This is consistent with Fong et al. (2010) who find evidence that mainland

Table 9
Bivariate and multi-variate Fama–MacBeth regression results with MAX, 6-month holding period.
Each month from 1997:01 to 2014:12 we run a firm-level bivariate and multi-variate Fama–MacBeth cross-sectional regression of the 6-month return ($t+1$ to $t+6$) with 1-month lagged values (t) of the MAX and other control variables. Each row reports the time-series averages of the slope coefficients and their associated Newey–West *t-statistics*. MAX and the other control variables are defined in Table 2. The symbol *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

MAX	*Size*	*BM*	*Momentum*	*Rev*	*CP*	*SSKEW*	*ISKEW*	*IV*	*ILLIQ*	*BETA*
−0.556***	−0.020***									
(−9.088)	(−2.646)									
−0.535***		0.044**								
(−8.676)		(2.223)								
−0.523***			−0.012							
(−8.727)			(−0.380)							
−0.587***				−0.008						
(−8.390)				(−0.224)						
−0.514***					−0.002					
(−8.785)					(−1.407)					
−0.554***						0.001				
(−7.930)						(0.230)				
−0.561***							−0.000			
(−6.407)							(−0.014)			
−0.292***								−1.760***		
(−3.755)								(−4.065)		
−0.519***									58.676***	
(−6.878)									(4.031)	
−0.567***										0.007
(−7.901)										(0.324)
−0.155**	−-0.017**	0.045***	0.004	0.013	−0.001	0.005***	−0.003*	−1.623***	37.543***	−0.007
(−2.164)	(−2.534)	(3.184)	(0.179)	(0.406)	(−0.688)	(2.731)	(−1.726)	(−5.613)	(4.331)	(−0.557)

Table 10
Bivariate and multi-variate Fama–MacBeth regression results with MAX, 6-month holding period: Size group and Sub-period sample.
We firstly sort stocks into three portfolios by Size, namely SMA, small-, MED, medium-, and BIG, big-size portfolio. Each month from 1997:01 to 2014:12 we run a firm-level multivariate Fama–MacBeth cross-sectional regression of the 6-month return ($t+1$ to $t+6$) with 1-month lagged values (t) of the MAX and other control variables. Each column reports the time-series averages of the slope coefficients and their associated Newey-West *t-statistics*. We also divide our testing period into two sub-sample periods, from 1997 to 2004 and from 2005 to 2014, and repeat the test above. MAX and the other control variables are defined in Table 2. The symbol *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	Six month holding period return				
	SMA	MED	BIG	1997–2004	2005–2014
MAX	−0.094	−0.111	**−0.270*** **	−0.092	**−0.176** **
	(−0.849)	(−1.529)	**(−2.954)**	(−0.598)	**(−2.205)**
Size	−0.028**	−0.026***	−0.014**	−0.017	−0.017**
	(−2.003)	(−2.603)	(−2.144)	(−1.519)	(−2.085)
BM	0.069***	0.035**	0.042**	0.097***	0.028*
	(3.652)	(2.531)	(2.198)	(4.150)	(1.703)
Momentum	−0.009	0.001	0.017	0.084***	−0.023
	(−0.332)	(0.062)	(0.705)	(4.652)	(−0.780)
Rev	−0.007	0.014	0.035	0.091***	−0.014
	(−0.175)	(0.424)	(0.965)	(2.683)	(−0.355)
CP	−0.007**	−0.002	−0.000	−0.001	−0.001
	(−2.072)	(−1.438)	(−0.078)	(−0.786)	(−0.490)
SSKEW	0.004***	0.004***	0.007***	0.004**	0.005**
	(2.740)	(2.755)	(2.709)	(2.312)	(2.198)
ISKEW	−0.003	0.000	−0.002	−0.006***	−0.001
	(−1.538)	(0.231)	(−0.685)	(−4.268)	(−0.657)
IV	−1.712***	−2.033***	−1.055***	−2.299***	−1.387***
	(−4.201)	(−5.698)	(−2.899)	(−4.805)	(−4.063)
ILLIQ	28.981***	34.390***	35.649**	1.375	50.158***
	(3.802)	(3.532)	(2.365)	(0.800)	(4.687)
BETA	0.014	−0.003	−0.013	0.005	−-0.012
	(1.121)	(−0.181)	(−0.701)	(0.376)	(−0.668)
Intercept	0.531***	0.491***	0.297**	0.207	0.400***
	(2.977)	(3.218)	(2.536)	(1.259)	(3.450)

Chinese investors are more speculative and have higher risk appetites than Hong Kong and international investors. In an earlier study, Ma (1996) also documents evidence of risk-seeking behavior among mainland Chinese investors by establishing a positive relationship between share prices and domestic beta risk. In the psychology literature, Raylu and Oei (2004) report that gambling is an acceptable form of social activity in Chinese communities while in a related study, Loo et al. (2008) find widespread social gambling among Chinese communities as it is a preferred form of entertainment. The results of both studies suggest a predisposition among Chinese investors to prefer lottery-like stocks.

4. Concluding remarks

Motivated by Bali et al.'s (2011) findings of a significant role of extreme returns in the U.S. stock markets, we investigate the existence of the same in the world's largest emerging market. Insofar as the Chinese stock markets have been characterised as highly speculative, with the extant literature indicating a predisposition among Chinese investors to prefer riskier stocks, there is reason to believe that the negative MAX effect would also be evident in this market. We find evidence of a MAX effect in returns over a 1-month holding period and even when we extend the holding period to three and 6 months. This suggests that there is a relatively long lag in the price adjustment back to fundamental levels in the Chinese stock markets. We also find that the MAX effect does not weaken, much less reverse the IV effect in the Chinese stock market contrary to the findings of Annaert et al. (2013) in European markets and of Bali et al. (2011) in U.S. stock markets. Our results suggest that both the MAX effect and the anomalous IV effect are separate effects and can coexist at least in the Chinese stock markets. Our results underscore the importance of country verification, especially in emerging markets, of apparent anomalies initially discovered in developed stock markets. To the extent that high MAX stocks are lottery-like, and interpreted along with the strong evidence of risk-seeking behaviour among Chinese investors, our results partially support the suggestion of Bali et al. (2011) that the negative MAX effect could be driven by investor preference for stocks with lottery-like features.

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Appendix A. Construction of Fama–French three factors

We follow Fama and French's (1993) method to construct FF-3 factors for the Chinese stock markets. The market factor in month t is a value-weighted average market return across all sample stocks. The SMB and HML factors are constructed using six value-weighted portfolios formed on Size and BM. At the end of each June, stocks are independently ranked by Size and BM, and then portfolios are intersections of two portfolios formed by Size and three portfolios formed by BM. Portfolios are reformed every month. We use median point to sort stocks into two portfolios, big- and small-size portfolios; and the BM breakpoints are the top 33th and 67th percentiles. Therefore, six Size-BM portfolios are formed, namely big-high, big-medium, big-low, small-high, small-medium, and small-low. The SMB factor is the difference of the average return between the three small-size portfolios and the three big-size portfolios. The HML factor is the difference of average return between the two top 33.33% high-BM portfolios and the two bottom 33.33% low-BM portfolios. Table A shows the descriptive statistics of the FF three factors, and Table B shows the correlation matrix of the three factors respectively

Table 1A
Descriptive statistics for the Fama–French three factors.

	Market	SMB	HML
Average return	0.93%	0.82%	0.19%
t-Statistic	1.59	2.98	0.95
Minimum	−26.85%	−17.30%	−11.81%
25th percentile	−5.04%	−1.51%	−1.27%
Median	0.73%	1.12%	0.21%
75th percentile	5.23%	3.42%	1.91%
Maximum	36.29%	10.08%	14.84%
Skewness	0.33	−0.55	−0.11
Kurtosis	4.67	4.51	7.27

Table 1B
Correlation matrix for the Fama–French three factors.

	Market	SMB	HML
Market	1.00	0.07	0.03
SMB	0.19	1.00	−0.24
HML	0.04	−0.25	1.00

Note: Numbers above the diagonal are Pearson product moment correlation coefficients, while numbers below the diagonal are Spearman rank correlation coefficients.

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