International Review of Economics and Finance 53 (2018) 1–15

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market

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ARTICLE INFO

JEL classification:
G02
G12
G17

Keywords:
Idiosyncratic volatility anomaly
Extreme returns
Investor behavioral biases
Limits to arbitrage
The Chinese stock market

ABSTRACT

The literature documents that the IVOL anomaly is subsumed by the MAX effect in U.S. and European stock market. Consistent with the literature, we find strong IVOL and MAX effects in the Chinese stock market. However, we show that the IVOL anomaly is not subsumed by the MAX effect, instead the MAX effect is subsumed by the IVOL anomaly. We interpret our findings as evidence that the IVOL anomaly in the Chinese stock market is beyond the effect of typical investor behavioral biases and there are stronger limits to arbitrage in the Chinese stock market due to unique institutional settings.

1. Introduction

Under classical asset pricing models, stock returns should be uncorrelated with idiosyncratic volatility since idiosyncratic volatility can be diversified away. Merton (1987) notes that in an information-segmented market, the relation between stock return and idiosyncratic volatility may be positive as investors may hold imperfectly diversified portfolios and thus require higher returns for stocks with higher firm-specific risk. Some behavioral models, such as Barberis and Huang (2001), also predict that high idiosyncratic volatility stocks earn high expected returns. Based on portfolios formed on idiosyncratic volatility, earlier researchers either find a significantly positive or insignificant relation between idiosyncratic volatility and average returns (e.g., Lehmann, 1990; Malkiel & Xu, 2002).

However, Ang, Hodrick, Xing, and Zhang (2006) document that at the individual stock level, stocks with high idiosyncratic volatility on average have low future returns in the U.S. stock market. The relation is referred to as the IVOL anomaly in subsequent studies. The IVOL anomaly is robust to controlling for various stock characteristics, and cannot be explained by trading frictions, higher moments of returns such as skewness, or asymmetric information among investors. Several studies have also documented a significant IVOL anomaly in the Chinese stock market.[1]

The literature has proposed a number of potential explanations of the IVOL anomaly.[2] In particular, Bali, Cakici, and Whitelaw (2011) documents a significant MAX effect in the U.S. market. Using extreme positive return (MAX) as a proxy for lottery-type payoff, they find that stocks with the lowest MAX outperform stocks with the highest MAX by as much as 1.03% per month. More importantly,

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[1] See, for example, Drew et al. (2004), Eun and Huang (2007), Nartea et al. (2013), and Gu et al. (2014).

[2] Such as explanations based on the difference of investor opinion and the effect of short-sale constraints on stock prices (Boehme, Danielsen, Kumar, & Sorescu, 2009), selective corporate disclosure (Jiang, Xu, & Yao, 2009), short-term return reversals (Huang, Liu, Rhee, & Zhang, 2009), the effect of market microstructure (Han & Lesmond, 2011; Avramov, Chordia, Jostova, & Philipov, 2013), and the asymmetric limits to arbitrage (Stambaugh, Yu, & Yuan, 2015).

https://doi.org/10.1016/j.iref.2017.10.015
Received 17 August 2016; Received in revised form 7 October 2017; Accepted 10 October 2017
Available online 12 October 2017
1059-0560/

they find that the IVOL anomaly is subsumed by the MAX effect. They interpret the findings as evidence that the IVOL anomaly is driven by investors' preference for lottery-like stocks in the U.S. equity market and such behavioral bias is consistent with the cumulative prospect theory (Barberis & Huang, 2008; Tversky & Kahneman, 1992). Subsequent studies by Annaert, De Ceuster, and Verstegen (2013) and Walkshäusl (2014) further confirm the relation between the IVOL and MAX effects using data from the European equity markets. Nevertheless, using data from South Korea, a relatively advanced emerging market, Nartea, Wu, and Liu (2014) find that the IVOL effect does not subsume the MAX effect. Instead, the IVOL and MAX are two independent effects in the South Korean market.

It is known that the Chinese stock market is dominated by individual investors (Ng & Wu, 2007; Tan, Chiang, Mason, & Nelling, 2008; Jiang, Lu, & Zhu, 2014; Yao, Ma, & He, 2014). Individual investors do not invest in well-diversified portfolios (Calvet, Campbell, & Sodini, 2007; Mitton & Vorkink, 2007; Goetzmann & Kumar, 2008) and exhibit a preference for stocks with lottery-like payoffs (Chan & Chui, 2016; Kumar, 2009). Moreover, the literature documents that Chinese have a strong tendency of gambling (Loo, Raylu, & Oei, 2008; Tse, Yu, Rossen, & Wang, 2010). Motivated by the above literature, we conjecture that there is a strong MAX effect in the Chinese stock market and such effect may subsume the IVOL effect. In addition, there is also evidence that individual investors tend to engage in contrarian investing strategies, i.e., buying stocks with substantial drops in prices (Kaniel, Saar, & Titman, 2008). Such contrarian behavior could induce a negative relation between the extreme negative return (MIN) and future stock returns (the MIN effect). In this paper, we examine whether there are significant MAX and MIN effects in the Chinese stock market and, more importantly, the relations between the IVOL effect and the MAX or MIN effect.

Consistent with the literature, we find a significant IVOL anomaly in the Chinese stock market. In addition, consistent with studies based on developed markets (Bali et al., 2011; Annaert et al., 2013; and; Walkshäusl, 2014) and emerging markets (Nartea et al., 2014; Carpenter, Lu, & Whitelaw, 2015), we find a significant MAX effect in the Chinese stock market. That is, investors in the Chinese stock market also exhibit preference for lottery-like stocks. We also find a MIN effect, albeit weaker compared to the MAX effect, in the Chinese stock market. That is, investors in the Chinese stock market exhibit a tendency of chasing stocks with extreme negative returns. These findings suggest that investors in the Chinese stock market are subject to typical behavioral biases.

However, our results show that the IVOL anomaly is not subsumed by the MAX effect or the MIN effect in the Chinese stock market. The negative relation between IVOL and future stock returns remains significant even if we include MAX and MIN as control variables. This finding is in contrast with studies by Bali et al. (2011), Annaert et al. (2013), and Walkshäusl (2014) who show that the IVOL anomaly is subsumed by the MAX effect in the U.S. and European equity markets. It confirms the finding documented in Nartea et al. (2014) who find that the IVOL and MAX are two independent effects in the South Korean stock market. Moreover, we find evidence that the MAX effect is subsumed by the IVOL effect. The negative relation between MAX and future stock returns becomes insignificant once we include IVOL as a control variable. In addition, the MIN effect is largely reversed when IVOL is included as a control variable.

Our empirical findings suggest that the IVOL anomaly in the Chinese stock market is beyond the effect of typical investor behavioral biases. Despite the finding that investors in the Chinese stock market exhibit strong behavioral biases, as evidenced in the MAX and MIN effects, such behavioral biases do not fully explain the IVOL anomaly. We interpret our findings from the perspective of unique institutional settings in the Chinese stock market. Although the Chinese stock market is among the largest in the world,[3] it remains at its development stage with high market frictions. For instance, the Chinese stock market imposes daily price limits of stock price changes. There was strict restriction on short selling prior to March 31, 2010.[4] Moreover, there is also higher level of information asymmetry due to poor corporate governance and low analyst coverage. Such unique institutional features lead to strong market frictions in the Chinese stock market. As argued in Shleifer and Vishny (1997), strong market frictions and high idiosyncratic volatility, a proxy for limits to arbitrage, may prevent sophisticated investors from arbitraging away anomalous stock returns. As such, stock return anomalies such as the IVOL anomaly are likely driven by factors beyond the effect of investor behavioral biases.

The rest of the paper is organized as follows. Section 2 describes data and variable construction. Section 3 examines the IVOL anomaly, the MAX effect, and the MIN effect in the Chinese stock market as well as the relations among these anomalies. Section 4 performs further analyses during different investor sentiment states. Section 5 concludes.

2. Data and variable construction

2.1. Data

We obtain information on daily and monthly stock returns and information on financial statements from the China Stock Market and Accounting Research (CSMAR) database. The Fama-French-Carhart four factors, i.e. RMRF, SMB, HML, and WML, are obtained from RESSET database which is a financial information and service provider in China (http://www.resset.cn/).[5] The Consumer Confidence Index (CCI) data is downloaded from Wind, which is a leading provider of financial data and solutions in China.

[3] By the end of 2015, the market capitalizations of Shanghai Stock Exchange and Shenzhen Stock Exchange are, respectively, $ 4.55 trillion and $ 3.64 trillion, ranking 4th and 5th respectively among the world stock exchanges according to the WFE annual statistics guide 2015.

[4] The restrictions have since been slightly relaxed to allow stocks on a designated list to be bought on margin and/or sold short. The list covered only 90 constituent stocks initially and was subsequently revised and finally expanded to include 900 stocks in September 2014.

[5] Specifically, RMRF is the excess return on a value-weighted portfolio of all A-share stocks. Same as the Fama-French factor construction, size factor (SMB) is the difference in value-weighted average return between the three small-stock portfolios (S/L, S/M, and S/H) and the three big-stock portfolios (B/L, B/M, and B/H). Book-to-market factor (HML) is the difference in value-weighted average return between the two high-BE/ME portfolios (S/H and B/H) and the two low-BE/ME portfolios (S/L and B/L). Momentum Factor (WML) is constructed as the difference in value-weighted average return between the 30 percent of stocks with the highest eleven-month returns (lagged by one month) or winners and the 30 percent of stocks with the lowest eleven-month returns (lagged by one month) or losers.

We focus on the A-shares listed in both the Shanghai and Shenzhen stock exchanges. The sample period is from January 1997 to December 2014. We exclude stocks under special treatment,[6] stocks on the second-board market, and stocks with less than 250 trading days. Special cases that are not subjected to daily price limits, such as a stock' initial public offering (IPO) day, are also excluded.

2.2. Variable construction

The variables used in our analysis are defined as follows. Idiosyncratic volatility (IVOL) is the idiosyncratic volatility relative to the Fama and French (1993) three-factor model using daily stock returns over the previous month (Ang et al., 2006). As in Bali et al. (2011), MAX is the maximum daily stock return over the previous month; MAX5 is the average of the five highest daily returns over the previous month; MIN is the minimum daily return in previous month multiplied by minus one; MIN5 is defined as the average of the five lowest daily returns over the previous month multiplied by minus one. A firm's size (SIZE) is the natural logarithm of circulation market equity (stock price multiplied by the number of liquid shares outstanding). Book-to-market (BM) is the ratio of book equity to market equity for the fiscal year ending in the previous calendar year. Momentum (MOM) is the cumulative prior twelve-month stock return, skipping the most recent month (Jegadeesh & Titman, 1993). Short-term reversal (REV) is the lagged one-month return (Jegadeesh, 1990). Illiquidity (ILLIQ) is the absolute monthly stock return divided by its trading volume in RMB (Amihud, 2002), scaled by 10^9. Following Scholes and Williams (1977) and Dimson (1979), we use the lag and lead of the market portfolio as well as the current market when estimating beta:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}\left(R_{m,d-1} - r_{f,d-1}\right) + \beta_{2,i}\left(R_{m,d} - r_{f,d}\right) + \beta_{3,i}\left(R_{m,d+1} - r_{f,d+1}\right) + \varepsilon_{i,d} \tag{1}$$

where $R_{i,d}$ is stock *i's* return on day *d*, $R_{m,d}$ is the market return on day *d*, and $r_{f,d}$ is the risk-free rate on day *d*. The market beta (BETA) of stock *i* in month *t* is defined as:

$$\widehat{\beta}_{\mathrm{i}} = \widehat{\beta}_{1,\mathrm{i}} + \widehat{\beta}_{2,\mathrm{i}} + \widehat{\beta}_{3,\mathrm{i}} \tag{2}$$

Following Bali et al. (2011), we estimate the following regression for each stock:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i\left(R_{m,d} - r_{f,d}\right) + \gamma_i\left(R_{m,d} - r_{f,d}\right)^2 + \varepsilon_{i,d} \tag{3}$$

Idiosyncratic skewness (ISKEW) of stock *i* in year *t* is defined as the skewness of daily residuals $\varepsilon_{i,d}$ in year *t*. Co-skewness (COSKEW) of stock *i* in year *t* is the estimated slope coefficient γ_i.[7]

Panel A of Table 1 reports the number of stocks year by year in our sample period from 1997 to 2014. On average, there are 1460 stocks per year, ranging from 720 in 1997 to 2137 in 2014. Panel B of Table 1 presents summary statistics for the variables. The mean of IVOL, MAX, and MIN are 0.02, 0.06, and 0.05 respectively. Panel C of Table 1 reports the average monthly cross-sectional correlations of IVOL, MAX, MAX5, MIN, MIN5, SIZE, BETA, BM, REV, MOM, ILLIQ, ISKEW, and COSKEW. The correlation is 0.45(0.27) between IVOL and MAX (MIN). It is lower than that in Bali et al. (2011) which is 0.7533 (0.7554) between IVOL and MAX (MIN).

3. The IVOL anomaly, the MAX and MIN effects

3.1. The IVOL anomaly

Ang et al. (2006, 2009) find that there is a negative relation between idiosyncratic volatility and future stock returns, known as the IVOL anomaly, in the U.S. market as well as in international developed markets. Examining all firms listed in the Shanghai stock exchange, Drew, Naughton, and Veeraraghavan (2004) find that small and low-idiosyncratic volatility firms generate superior returns relative to big and high-idiosyncratic volatility firms. Similarly, Eun and Huang (2007) document a significant and negative relationship between idiosyncratic volatility and future stock returns. Nartea, Wu, and Liu (2013) and Gu, Kang, and Xu (2014) also provide evidence of an IVOL anomaly in the Chinese stock market.

3.1.1. Univariate portfolio-level analysis

In this section, we examine whether there is a significant IVOL anomaly in the Chinese stock market during our sample period. Following Ang et al. (2006), we sort stocks into quintile portfolios, based on idiosyncratic volatility, estimated under the Fama and French (1993) three-factor model from daily returns over the past month, and then hold these portfolios for one month. The portfolios are rebalanced monthly.

Table 2 presents the average monthly returns and the Fama-French-Carhart (1997) four-factor (FF-4) alphas on the equal-weighted (EW) and value-weighted (VW) quintile portfolios. Q1(5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatility. The EW average raw return difference between Q5 and Q1 is −1.48% per month with a West and Newey (1987) t-statistic of −7.46. The difference in FF-4 alpha between high and low IVOL portfolios is −1.53% per month with a Newey-West t-statistic of −8.09. Both differences are economically and statistically significant at all conventional levels. The average raw returns decrease from 2.01% per

[6] Since December 16, 1996, the Shanghai and Shenzhen Stock Exchanges have established a daily price limit for trading in stocks and mutual funds. The daily price limit is 10% for normal stocks and is 5% for stocks under special treatment.

[7] I wish to thank the referee for the suggestion of including the idiosyncratic skewness and co-skewness as additional control variables in our analysis.

Table 1
Descriptive statistics.

Panel A: Number of stocks by year.

year	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
N	720	826	924	1061	1140	1207	1267	1363	1366	1418	1517	1577	1644	1867	2020	2101	2115	2137

Panel B: Descriptive Statistics.

Variable	Mean	Median	5^{th} percentile	95^{th} percentile	Std
IVOL	0.02	0.02	0.01	0.03	0.02
MAX	0.06	0.05	0.03	0.13	0.05
MAX5	0.03	0.03	0.02	0.06	0.01
MIN	0.05	0.05	0.03	0.08	0.02
MIN5	0.03	0.03	0.02	0.05	0.01
SIZE	14.05	13.95	12.81	15.64	0.88
BETA	1.05	1.04	−0.29	2.41	0.86
BM	0.53	0.51	0.22	0.86	0.25
REV	0.02	0.00	−0.12	0.19	0.11
MOM	0.17	0.13	−0.28	0.74	0.32
ILLIQ	0.83	0.34	0.02	1.73	9.28
ISKEW	0.54	0.50	−0.36	1.50	0.79
COSKEW	−3.08	−3.32	−8.90	3.45	3.83

Panel C: Correlation matrix.

	IVOL	MAX	MAX5	MIN	MIN5	SIZE	BETA	BM	REV	MOM	ILLIQ	ISKEW	COSKEW
IVOL	1.00	**0.45**	**0.44**	**0.27**	**0.29**	**−0.07**	**0.03**	**−0.07**	**0.13**	**0.11**	**0.00**	**−0.03**	**−0.04**
MAX		1.00	**0.69**	**0.13**	**0.17**	**−0.04**	**0.18**	**−0.03**	**0.04**	**0.03**	−0.01	0.00	**−0.04**
MAX5			1.00	**0.23**	**0.29**	**−0.05**	**0.21**	**−0.03**	**0.06**	**0.05**	**−0.04**	−0.01	**−0.06**
MIN				1.00	**0.74**	**−0.14**	**0.23**	**−0.04**	**0.11**	**0.05**	**−0.05**	**−0.02**	**−0.07**
MIN5					1.00	**−0.16**	**0.31**	**−0.05**	**0.13**	**0.07**	**−0.09**	**−0.02**	**−0.08**
SIZE						1.00	**−0.03**	**0.09**	**0.04**	**0.18**	**−0.28**	**0.03**	**0.28**
BETA							1.00	**0.02**	−0.02	**−0.03**	**−0.03**	**0.01**	**−0.04**
BM								1.00	0.00	**−0.16**	**−0.05**	**0.07**	**−0.09**
REV									1.00	**−0.02**	**−0.03**	0.00	**−0.01**
MOM										1.00	**−0.10**	**0.03**	**0.07**
ILLIQ											1.00	**−0.01**	**−0.05**
ISKEW												1.00	**−0.07**
COSKEW													1.00

Notes: Panel A reports the number of stocks (N) each year in our sample period. Panel B reports summary statistics of idiosyncratic volatility (IVOL), maximum daily return in previous month (MAX), the average of the five highest daily returns in previous month (MAX5), minimum daily return in previous month multiplied by minus one (MIN), the average of the five lowest daily returns in previous month multiplied by minus one (MIN5), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). Each month we compute the cross-sectional mean, median, standard deviation, 5th, and 95th percentiles of the above variables. The table reports the time series averages of these statistics. Panel C reports the time-series average of the cross-sectional correlations between variables. The bold font indicates significance at 5% level. The sample period is from January 1997 to December 2014.

Table 2
Average returns and alphas of portfolios sorted by IVOL.

Quintile	EW Portfolios		VW Portfolios	
	Average return	FF-4 alpha	Average return	FF-4 alpha
Q1 (Low IVOL)	2.01	0.61	1.17	0.35
2	1.98	0.54	1.41	0.45
3	1.72	0.29	1.25	0.33
4	1.41	−0.05	1.15	0.16
Q5 (High IVOL)	0.53	−0.92	0.49	−0.65
Q5-Q1	−1.48	−1.53	−0.68	−1.00
	(−7.46)	(−8.09)	(−2.47)	(−3.97)

Notes: Each month quintile portfolios are formed by sorting stocks based on IVOL over the past one month. Q1 (5) is the portfolio of stocks with the lowest (highest) IVOL. This table reports average monthly returns and the four-factor Fama-French-Carhart (1997) (FF-4) alphas (in percentage term) on the equal-weighted (EW) and value-weighted (VW) portfolios. The table also reports the differences in monthly returns and FF-4 alphas between quintiles 5 and 1 as well as the West and Newey (1987) t-statistics (in parentheses). The sample period is from January 1997 to December 2014.

month for low IVOL portfolio to 0.53% per month for high IVOL portfolio. The FF-4 alphas decrease from 0.61% per month for low IVOL portfolio to −0.92% per month for high IVOL portfolio. For the VW portfolios, the results are similar. The average raw return difference between low and high IVOL portfolios is −0.68% per month (t-stat = −2.47) and the corresponding difference in FF-4 alphas is −1.00% per month (t-stat = −3.97). The results show that consistent with the literature, there is a significant IVOL anomaly in the Chinese stock market during our sample period.

3.1.2. Robustness check: double sorts

In unreported results, we show that IVOL is related to other firm characteristics, such as size, book-to-market, illiquidity, idiosyncratic skewness, and co-skewness. The literature documents that these variables also have predictive power of returns. To ensure that the results reported in Table 2 are robust to controlling for other firm characteristics, we perform double sorts on the control variable and idiosyncratic volatility. Following Bali et al. (2011), we first sort the stocks into quintiles using the control variable, then within each quintile, we sort stocks into quintile portfolios ranked based on the idiosyncratic volatility (IVOL) so that Q1(5) contains stocks with the lowest (highest) IVOL. For brevity, we report the average returns across the five control quintiles to produce quintile portfolios with dispersion in idiosyncratic volatility but with similar levels of the control variable. For example, the first column of Table 3 reports returns averaged across five portfolios to produce quintiles with dispersion in IVOL, but with similar levels of firm size.

Table 3 presents the return differences between high and low IVOL portfolios after controlling for firm size, market beta, book-to-market, short-term reversals, momentum, illiquidity, idiosyncratic skewness, and co-skewness. As shown in Panel A, the EW average return differences between the high and low IVOL portfolios are −1.63%, −1.45%, −1.52%, −1.47%, −1.51%, −1.50%, −1.55%, and −1.53% per month, respectively. These average raw return differences are both economically and statistically significant at all conventional levels. The corresponding values for the EW FF-4 alpha differences are −1.58%, −1.52%, −1.59%, −1.59%, −1.60%, −1.64%, −1.53%, and −1.53%, which are also highly significant. As reported in Panel B, the VW average return differences between high and low portfolios are −0.69%, −0.60%, −0.67%, −0.61%, −0.72%, −0.64%, −0.78%, and −0.68% per month, respectively. These average raw return differences are all significant at 5% level. The corresponding values for the value-weighted average risk-adjusted return differences are −0.92%, −0.90%, −1.07%, −0.98%, −1.15%, −1.04%, −1.04%, and −1.04%, which are all significant at all conventional levels. These results indicate that for both EW and VW portfolios the well-known cross-sectional effects such as size, book-to-market, short-term reversal, momentum, illiquidity, skewness cannot explain the low returns to high IVOL stocks.

3.1.3. Robustness check: Fama-MacBeth regressions

The bivariate sorts confirm the significance of the idiosyncratic volatility as a determinant of the cross-section of future returns after controlling for a specific firm characteristic. In this section, we perform the following Fama and MacBeth (1973) regressions with different firm characteristics included as control variables:

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \beta_{j,t} Control_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \sum \beta_{j,t} Control_{i,t} + \varepsilon_{i,t+1} \tag{6}$$

Table 3
Returns on portfolios sorted by IVOL controlling for SIZE, BETA, BM, REV, MOM, ILLIQ, ISKEW, and COSKEW.

Quintile	SIZE	BETA	BM	REV	MOM	ILLIQ	ISKEW	COSKEW
Panel A: Equal-weighted portfolios.								
Q1 (Low IVOL)	2.06	2.00	1.98	1.93	2.02	1.99	2.01	2.02
2	1.82	1.79	1.90	1.88	1.93	1.82	1.95	1.89
3	1.65	1.64	1.65	1.66	1.65	1.68	1.61	1.67
4	1.28	1.26	1.30	1.33	1.30	1.27	1.32	1.25
Q5 (High IVOL)	0.43	0.54	0.46	0.46	0.52	0.49	0.46	0.50
Return difference	−1.63	−1.45	−1.52	−1.47	−1.51	−1.50	−1.55	−1.53
	(−9.07)	(−8.25)	(−8.19)	(−8.09)	(−8.58)	(−7.83)	(−7.57)	(−7.49)
Alpha difference	−1.58	−1.52	−1.59	−1.59	−1.60	−1.64	−1.53	−1.53
	(−7.79)	(−8.60)	(−8.07)	(−8.91)	(−9.24)	(−8.44)	(−7.65)	(−7.49)
Panel B: Value-weighted portfolios.								
Q1 (Low IVOL)	1.14	1.11	1.12	1.03	1.19	1.13	1.12	1.09
2	1.33	1.24	1.34	1.43	1.43	1.35	1.44	1.45
3	1.11	1.24	1.22	1.24	1.10	1.21	0.99	1.11
4	1.07	1.05	1.05	1.09	1.00	0.98	1.20	1.08
Q5 (High IVOL)	0.45	0.51	0.46	0.42	0.47	0.49	0.35	0.42
Return difference	−0.69	−0.60	−0.67	−0.61	−0.72	−0.64	−0.78	−0.68
	(−2.50)	(−2.08)	(−2.33)	(−2.15)	(−2.60)	(−2.26)	(−2.66)	(−2.29)
Alpha difference	−0.92	−0.90	−1.07	−0.98	−1.15	−1.04	−1.04	−1.02
	(−3.19)	(−3.22)	(−3.56)	(−3.58)	(−4.39)	(−3.82)	(−3.57)	(−3.28)

Notes: Each month we first sort the stocks into quintiles by firm size (SIZE), market beta (BETA), book-to-market (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), or co-skewness (COSKEW). Then within each quintile, we further sort stocks into quintiles based on idiosyncratic volatility (IVOL). The double-sorted equal-weighted (Panel A) and value-weighted (Panel B) quintile portfolios are formed every month from January 1997 to December 2014. This table presents average returns across the five control portfolios to produce quintiles with dispersion in IVOL but with similar levels of the control variable. Q1 (5) contains stocks with the lowest (highest) IVOL. The table also reports differences in average raw returns and FF-4 alphas between the high and low IVOL portfolios as well as their West and Newey (1987) t-statistics (in parentheses).

where $R_{i,t+1}$ is the realize return on stock i in month $t+1$. $IVOL_{i,t}$ is the idiosyncratic volatility relative to the Fama and French (1993) three-factor model of stock i in month t. $Control_{i,t}$ is control variable, including: firm size (SIZE), market beta (BETA), book-to-market (B/M), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). α is the intercept, γ_0 and β_j are coefficients, and ε is the residual.

Table 4 reports the time-series averages of the slopes, their West and Newey (1987) t-statistics, and adjusted R^2. The average slope of IVOL in the univariate regression (specification(1) of Table 4) is −0.855 with a Newey-West t-statistic of −8.92. The average slope of IVOL remains negative and statistically significant in the bivariate regressions (specifications (2)–(9) of Table 4), indicating that none of the control variables can explain the IVOL anomaly individually, which is consistent with the bivariate portfolio-level analysis in Table 3. More importantly, the average slope of IVOL is −0.898 with a Newey-West t-statistic of −11.39 in the multivariate regression (specification (10) of Table 4), evidence that the predictive power of stock returns by IVOL is robust to controlling for other firm characteristics.

In short, there is an economically and statistically significant negative relation between idiosyncratic volatility and future stock returns in the Chinese stock market, which is consistent with the findings on the developed markets (Ang et al., 2006; 2009) as well as the emerging markets (Nartea et al., 2013; Gu et al., 2014).

3.2. *The MAX and MIN effects*

Bali et al. (2011) document a statistically significant negative relation between extreme positive returns over the previous month (MAX), a proxy for lottery-type payoff, and future stock returns. They interpret the findings as evidence of investor behavioral biases consistent with the cumulative prospect theory (Barberis & Huang, 2008; Tversky & Kahneman, 1992). Using a broad sample of European equity markets, Annaert et al. (2013) and Walkshäusl (2014) provide supportive out-of-sample evidence on the MAX effect. Chan and Chui (2016) document the existence of a lottery-stock premium in the Hong Kong stock market. Therefore, they argue that stocks with high MAX or lottery-like payoffs are attractive to certain investors. In the meantime, arbitrageurs are discouraged from correcting potential mispricing due to high stock return volatility. As a consequence, these stocks are often overpriced and have lower future returns.

The Chinese stock market is dominated by individual investors. Based on 2014 data, 99.5% of A-share accounts in China are individual accounts and only 0.5% are institutional accounts. The literature shows that generally individual investors are not well-diversified in their investment portfolios. As shown in Kumar (2009), individual investors exhibit a preference for stocks with lottery-like payoffs. Gambling is widespread among Chinese people (Loo et al., 2008). Tse et al. (2010) find that compared to Western counterparts, Chinese people have elevated levels of gambling addiction and there is potential link between gambling and Chinese culture and history. Moreover, Kaniel et al. (2008) show that individuals tend to buy stocks with substantial drops in prices. As a result, stocks with extreme negative return (MIN) may be overpriced and have lower future returns. Motivated by the above literature, we conjecture that there is a strong MAX effect as well as MIN effect in the Chinese stock market.

Table 4
Firm-level cross-sectional return regressions on IVOL.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.028***	0.097***	0.024***	0.025***	0.027***	0.029***	0.024***	0.031***	0.027***	0.052*
	(3.71)	(3.35)	(3.03)	(3.40)	(3.32)	(3.61)	(2.95)	(3.67)	(3.43)	(1.97)
IVOL	−0.855***	−0.849***	−0.813***	−0.730***	−0.800***	−0.780***	−0.778***	−0.825***	−0.840***	−0.898***
	(−8.92)	(−9.62)	(−8.58)	(−8.11)	(−8.60)	(−8.31)	(−7.78)	(−8.48)	(−8.57)	(−11.39)
SIZE		−0.005***								−0.003
		(−2.49)								(−1.47)
BETA			0.004***							0.004***
			(3.51)							(4.29)
BM				0.006*						0.006*
				(1.72)						(1.71)
REV					−0.017**					0.000
					(−2.18)					(0.04)
MOM						0.001				0.008**
						(0.19)				(2.54)
ILLIQ							0.018***			0.015***
							(2.65)			(4.44)
ISKEW								−0.121*		−0.147***
								(−1.94)		(−2.61)
COSKEW									−0.060**	−0.005***
									(−2.08)	(−0.33)
Adj. R^2	1.84%	5.55%	2.94%	2.40%	2.97%	4.03%	3.11%	1.92%	2.54%	10.61%

Notes: Each month, we run firm-level cross-sectional regressions of stock returns on lagged predictor variables including idiosyncratic volatility(IVOL), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). This table reports the time-series averages of the cross-sectional regression coefficients, their associated West and Newey (1987) t-statistics (in parentheses), and Adjusted R^2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1997 to December 2014.

3.2.1. Univariate portfolio-level analysis

We form quintile portfolios by sorting the sample stocks based on the MAX or MIN in the previous month. The average monthly returns and the FF-4 alphas of the MAX or MIN portfolios are reported in Table 5. As shown in Panel A of Table 5, Q1 (5) contains the stocks with the lowest (highest) maximum daily returns over the previous month. The differences in average monthly return and FF-4 alpha between EW high and low MAX quintiles are −0.96% per month with a t-statistic of −5.63 and −1.07% per month with a t-statistic of −6.14, respectively. Both differences are economically and statistically significant at all conventional levels. The differences in average monthly return and FF-4 alpha between VW high and low MAX quintiles are −0.40% (t-stat = −1.35) and −0.61% (t-stat = −2.10), respectively. The results for the VW portfolios are relative weaker, but it is similar to Carpenter et al. (2015). In their paper, the average return and FF-4 alpha between VW high and low MAX quintiles are −0.38% (t-stat = −1.42) and −0.52% (t-stat = −1.85) in the Chinese stock market from March 1995 to December 2012. However, Bali et al. (2011) document that the results for EW portfolios are somewhat less economically and statistically significant in the U.S. stock market. The differences in average monthly return and FF-4 alpha between high and low MAX deciles are −1.03% (t-stats = −2.83) and −1.18% (t-stats = −4.71) for the VW portfolios and are −0.65% (t-stat = −1.83) and −0.66% (t-stat = −2.31) for the EW portfolios. The results of univariate-portfolio analysis in Panel A of Table 5 reveal a strong negative relationship between future stock returns and MAX, suggesting that investors may be willing to pay more for stocks that exhibit extreme positive returns, and thus, these stocks exhibit lower returns in the future.

In Panel B of Table 5, Q1 (5) is the stocks with the lowest (highest) MIN over the previous month. The EW and VW differences in average monthly return between high and low MIN portfolios are −0.13% per month with a t-statistic of −0.59 and −0.23% with a t-statistic of −0.83, respectively. The corresponding EW and VW differences in FF-4 alpha between high and low MIN portfolios are −0.38% with a t-statistic of −2.26 and −0.56% with a t-statistic of −2.19. The significant FF-4 alpha of MIN spread is due to significantly positive loadings on size factor. The univariate-portfolio analysis in Panel B of Table 5 shows that there is also a negative relationship between future stock returns and MIN.

3.2.2. Robustness check: bivariate sorts

Similar to our analysis on the IVOL anomaly, we examine whether the negative relation between MAX or MIN and the cross-section of future stock returns still holds once we control for various characteristics using bivariate portfolio sorts. Similarly, we first sort the stocks into quintiles using the control variable, then within each quintile, we sort stocks into quintile portfolios ranked based on MAX or MIN so that Q1 (5) contains stocks with the lowest (highest) MAX or MIN. For brevity, Table 6 reports the average returns across the five control quintiles to produce quintile portfolios with dispersion in MAX or MIN but with similar levels of the control variable.

Panel A of Table 6 presents the return differences between the EW high and low MAX portfolios after controlling for firm size, market beta, book-to-market, short-term reversal, momentum, illiquidity, idiosyncratic skewness, and co-skewness. The average return differences between high and low MAX are −1.03%, −1.10%, −1.06%, −1.00%, −1.04%, −0.95%, −0.96% and −1.03% per month, respectively. These average raw return differences are both economically and statistically significant. The corresponding FF-4 alpha differences are −1.16%, −1.19%, −1.18%, −1.25%, −1.19%, −1.14%, −1.08% and −1.15% per month, which are of high significance. For the VW portfolios, the return differences between high and low MAX are also significant. The results show that MAX effect is robust to the control variables.

Panel B of Table 6 presents the return differences between the EW high and low MIN portfolios after controlling for firm size, market

Table 5
Average returns and alphas of portfolios sorted by MAX or MIN.

Quintile	EW Portfolios		VW Portfolios	
	Average return	FF-4 alpha	Average return	FF-4 alpha
Panel A: Portfolios sorted by MAX.				
Q1 (Low MAX)	1.77	0.44	1.17	0.31
2	1.89	0.46	1.38	0.39
3	1.82	0.43	1.47	0.54
4	1.36	−0.03	1.01	0.03
Q5 (High MAX)	0.81	−0.63	0.77	−0.30
Q5-Q1	−0.96	−1.07	−0.40	−0.61
	(−5.63)	(−6.14)	(−1.35)	(−2.10)
Panel B: Portfolios sorted by MIN.				
Q1 (Low MIN)	1.53	0.17	1.27	0.39
2	1.51	0.09	1.36	0.26
3	1.58	0.04	1.11	0.00
4	1.62	0.00	1.08	−0.13
Q5 (High MIN)	1.40	−0.21	1.04	−0.17
Q5-Q1	−0.13	−0.38	−0.23	−0.56
	(−0.59)	(−2.26)	(−0.83)	(−2.19)

Notes: Each month quintile portfolios are formed by sorting stocks based on MAX or MIN over the past one month. Q1 (5) is the portfolio of stocks with the lowest (highest) MAX or MIN. This table reports the average monthly returns and the four-factor Fama-French-Carhart (1997) (FF-4) alphas (in percentage term) on the EW and VW portfolios. The table also reports differences in monthly returns and FF-4 alphas between quintile 5 and 1 as well as their West and Newey (1987) t-statistics (in parentheses). The sample period is from January 1997 to December 2014.

Table 6
Returns on portfolios sorted by MAX or MIN controlling for SIZE, BETA, BM, REV, MOM, ILLIQ, ISKEW, and COSKEW.

Quintile	SIZE	BETA	BM	REV	MOM	ILLIQ	ISKEW	COSKEW
Panel A: Sorted by MAX controlling for SIZE, BETA, BM, REV, MOM, ILLIQ, ISKEW, or COSKEW.								
Q1(Low MAX)	1.79	1.79	1.81	1.77	1.74	1.75	1.79	1.80
2	1.80	1.80	1.84	1.84	1.84	1.84	1.85	1.80
3	1.70	1.59	1.71	1.73	1.72	1.65	1.76	1.78
4	1.37	1.27	1.36	1.34	1.32	1.40	1.26	1.33
Q5(High MAX)	0.76	0.69	0.75	0.77	0.70	0.81	0.83	0.77
Return difference	−1.03	−1.10	−1.06	−1.00	−1.04	−0.95	−0.96	−1.03
	(−6.51)	(−7.25)	(−6.43)	(−6.30)	(−6.20)	(−5.38)	(−5.48)	(−5.81)
Alpha difference	−1.16	−1.19	−1.18	−1.25	−1.19	−1.14	−1.08	−1.15
	(−6.36)	(−6.99)	(−6.54)	(−7.79)	(−7.00)	(−6.19)	(−6.16)	(−6.09)
Panel B: Sorted by MIN controlling for SIZE, BETA, BM, REV, MOM, ILLIQ, ISKEW, or COSKEW.								
Q1(Low MIN)	1.57	1.62	1.57	1.62	1.36	1.58	1.48	1.48
2	1.47	1.41	1.48	1.47	1.47	1.50	1.45	1.44
3	1.63	1.55	1.56	1.60	1.55	1.62	1.56	1.54
4	1.58	1.51	1.58	1.60	1.58	1.61	1.64	1.66
Q5(High MIN)	1.40	1.30	1.47	1.44	1.37	1.40	1.37	1.38
Return difference	−0.17	−0.32	−0.10	−0.18	0.01	−0.18	−0.12	−0.11
	(−1.09)	(−1.72)	(−0.50)	(−0.91)	(0.05)	(−0.88)	(−0.53)	(−0.52)
Alpha difference	−0.30	−0.51	−0.30	−0.34	−0.26	−0.33	−0.35	−0.26
	(−1.99)	(−3.11)	(−1.69)	(−2.03)	(−1.58)	(−2.04)	(−2.06)	(−1.57)

Notes: Each month we first sort the stocks into quintiles by firm size (SIZE), market beta (BETA), book-to-market (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), or co-skewness (COSKEW). Then within each quintile, we further sort stocks into quintiles based on maximum/minimum daily return (MAX/MIN). The double-sorted equal-weighted quintile portfolios are formed every month from January 1997 to December 2014. This table presents average returns across the five control portfolios to produce quintiles with dispersion in MAX or MIN but with similar levels of the control variable. Q1 (5) contains stocks with the lowest (highest) MAX or MIN. The table also reports differences in average raw returns and FF-4 alphas between the high and low MAX or MIN portfolios as well as their West and Newey (1987) t-statistics (in parentheses).

beta, book-to-market, short-term reversal, momentum, illiquidity, idiosyncratic skewness, and co-skewness. Although, the average return differences between high and low MIN are insignificant, the corresponding FF-4 alpha differences are mostly significant, i.e., −0.30% (t-stat = −1.99), −0.51% (t-stat = −3.11), −0.30% (t-stat = −1.69), −0.34% (t-stat = −2.03), −0.26% (t-stat = −1.58), −0.33% (t-stat = −2.04), −0.35% (t-stat = −2.06) and −0.26% (t-stat = −1.57). The results show that the MIN effect is largely unaffected by the control variables.

3.2.3. *Robustness check: Fama-MacBeth regressions*

We further examine the relation between MAX or MIN and future stock returns while controlling for the effects of other firm characteristics by performing the following Fama and MacBeth (1973) regressions:

$$R_{i,t+1} = \alpha_t + \gamma_{1,t} MAX_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

$$R_{i,t+1} = \alpha_t + \gamma_{1,t} MAX_{i,t} + \sum \beta_{j,t} Control_{i.t} + \varepsilon_{i,t+1} \tag{8}$$

$$R_{i,t+1} = \alpha_t + \gamma_{2,t} MIN_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

$$R_{i,t+1} = \alpha_t + \gamma_{2,t} MIN_{i,t} + \sum \beta_{j,t} Control_{i.t} + \varepsilon_{i,t+1} \tag{10}$$

$$R_{i,t+1} = \alpha_t + \gamma_{1,t} MAX_{i,t} + \gamma_{2,t} MIN_{i,t} + \varepsilon_{i,t+1} \tag{11}$$

$$R_{i,t+1} = \alpha_t + \gamma_{1,t} MAX_{i,t} + \gamma_{2,t} MIN_{i,t} + \sum \beta_{j,t} Control_{i.t} + \varepsilon_{i,t+1} \tag{12}$$

The results are reported in Table 7. The average slope of MAX in the univariate regression (specification(1) of Table 7) is −0.156 with a t-statistic of −6.91, which is significant at 1% level. The average slope of MAX increases in both magnitude and statistical significance when the control variables are included in the regression (specification (2) of Table 7). The results indicate that there is a strong MAX effect in the Chinese stock market.

The average coefficient of future stock returns on MIN alone is negative but insignificant, i.e., −0.039 with a t-statistic of −1.40. It becomes significant in the multivariate regression (specification(4) of Table 7), i.e., −0.106 with a t-statistic of −3.57. Note that the original minimum returns are multiplied by −1 in constructing the variable MIN. The negative coefficient means that the more a stock falls in value, the lower the future return. The finding is different from Bali et al. (2011) who find that stocks with extreme negative

Table 7
Firm-level cross-sectional return regressions on MAX and MIN.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.022**	0.030	0.011	0.032	0.020***	0.031
	(3.21)	(1.13)	(1.55)	(1.24)	(2.95)	(1.19)
MAX	−0.156***	−0.144***			−0.171***	−0.139***
	(−6.91)	(−10.14)			(−8.46)	(−10.04)
MIN			−0.039	−0.106***	−0.006	−0.050
			(-1.40)	(−3.57)	(−0.14)	(−1.61)
SIZE		−0.002		−0.002		−0.002
		(−0.97)		(−1.25)		(−1.01)
BETA		0.005***		0.004***		0.005***
		(5.76)		(4.48)		(6.15)
BM		0.009**		0.010**		0.009**
		(2.16)		(2.35)		(2.22)
REV		−0.010		−0.009		−0.008
		(−1.63)		(−1.54)		(−1.38)
MOM		0.007**		0.006**		0.007**
		(2.21)		(2.00)		(2.28)
ILLIQ		0.020***		0.014***		0.019***
		(4.26)		(2.99)		(3.96)
ISKEW		−0.133**		−0.139**		−0.132**
		(−2.23)		(−2.30)		(−2.19)
COSKEW		0.004		0.007		0.004
		(0.25)		(0.46)		(0.28)
Adj. R^2	1.57%	10.60%	1.49%	10.41%	3.17%	11.15%

Notes: Each month, we run firm-level cross-sectional regressions of stock returns on lagged predictor variables including maximum/minimum daily return in the previous month (MAX/MIN), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). This table reports the time-series averages of the cross-sectional regression coefficients, their associated West and Newey (1987) t-statistics (in parentheses), and adjusted R^2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1997 to December 2014.

returns have higher future stock returns in the subsequent month in U.S. stock market. One unique feature of the Chinese stock market is that it is dominated by individual investors. Individual investors tend to engage in contrarian investing strategies, which could induce a negative relation between the extreme negative returns and future stock returns.

When MAX and MIN are both included in the regressions, the negative relation between MAX and future stock returns remains significant at all conventional levels. The average slope of MAX is −0.171 (t-stat = −8.46) in the bivariate regression and is −0.139 (t-stat = −10.04) in the multivariate regression. However, the negative relation between MIN and future stock returns becomes insignificant. We perform robustness checks to ensure that the results are not driven by potential outliers. We re-run the cross-sectional regressions by winsorizing MAX and MIN at the 99th and 95th percentiles to mitigate the effect of outliers and confirm that the results are consistent. As shown in Table 1, MAX and MIN are positively correlated. To provide an intuition of why MAX subsumes the predictive power of MIN for stock returns, we also computed the correlation between MAX and future stock returns and the correlation between MIN and future stock returns. Over our sample period, the average correlation between MAX and future stock returns is −0.031 with a standard error of 0.006, and the average correlation between MIN and future stock returns is −0.006 with standard error of 0.008. That is, MAX has a stronger relation with future stock returns and, as such, it subsumes the predictive power of MIN for stock returns.

In summary, similar to the findings by Bali et al. (2011), Annaert et al. (2013), Walkshäusl (2014) in the U.S. and European stock markets, and Nartea et al. (2014) and Carpenter et al. (2015) in the South Korean and Chinese stock markets, we find a strong MAX effect in the Chinese stock market during our sample period, indicating that there is a preference among Chinese investors for stocks with lottery-like payoffs. We also find that stocks with extreme negative returns have lower future returns in the subsequent month, which may be induced by individual investors' contrarian behavior in the Chinese stock market.

3.3. Is the IVOL anomaly driven by the MAX or MIN effect?

As shown in Bali et al. (2011), once the proxy for lottery-type payoff MAX is controlled, the negative IVOL-return relation is reversed in the U.S. stock market. They interpret the finding in the context of a market with poorly diversified yet risk-averse investors who have a preference for lottery-like assets. Namely, the IVOL anomaly is likely to be driven by investors' preference for lottery-like stocks. Using data from the European stock markets, Annaert et al. (2013) and Walkshäusl (2014) find that the IVOL anomaly is also subsumed by the MAX effect. Nartea et al. (2014) find that the MAX and IVOL effects are independent of each other in the South Korean stock market. Nartea, Kong, and Wu (2017) find that both the MAX and IVOL effects also independently coexist in the Chinese stock market. Based on further analysis on the relation between the MAX and IVOL effects during subsample periods of high versus low investor sentiment in the subsequent section, however, we draw different conclusions than those in Nartea et al. (2017).

In sections 3.1 and 3.2, we show that there is IVOL anomaly, MAX and MIN effects in the Chinese stock market. Interestingly, Han and Kumar (2008) provide evidence that the idiosyncratic volatility puzzle is concentrated in stocks dominated by individual investors. The Chinese stock market is dominated by individual investors, who are more likely to suffer from underdiversification and typical investor behavioral biases, providing an ideal setting for examining the relations between the IVOL effect and the MAX and MIN effects.

Bali et al. (2011) note that the stocks with extreme positive returns also have high idiosyncratic volatility. It is thus important to examine whether the IVOL effect is simply proxying for the MAX or MIN effect in the Chinese stock market. We conduct bivariate sorts to examine the relation between IVOL and MAX or MIN more closely. Specifically, we first sort the stocks into quintiles by control variable, then within each quintile, we sort stocks into quintiles based on the variable of interest. Table 8 presents the average returns across the five control portfolios to produce quintiles with dispersion in the variable of interest but with similar levels of the control variable.

Panel A of Table 8 reports the average returns across the five equal-weighted and value-weighted MAX or MIN portfolios to produce quintiles with dispersion in IVOL but with similar levels of MAX or MIN. The key statistics are the return and FF-4 alpha differences between the high IVOL (Q5) and low IVOL (Q1) portfolios. For the EW portfolios, when MAX is controlled, the difference between high and low IVOL quintiles in average raw return is −1.08% per month with a t-statistic of −6.39 and in FF-4 alpha is −1.04% per month with a t-statistic of −6.90. The magnitudes are much smaller than we have seen in Table 2. However, the result is not surprising, since MAX and IVOL are highly correlated, the spread in IVOL is significantly reduced after controlling for MAX. For the VW portfolios, after controlling for the MAX, the differences in average raw return and FF-4 alpha between high and low IVOL quintiles are less negative and significant. As shown in Table 2, the IVOL effect is much weaker in VW portfolios. For the EW portfolios, when MIN is controlled, the differences in average raw return and FF-4 alpha between high and low IVOL quintiles are −1.57% per month with a t-statistic of −9.06 and −1.59% per month with a t-statistic of −8.65, respectively. For the VW portfolios, after controlling for MIN, the differences in average raw return and FF-4 alpha between high and low IVOL portfolios are also less negative and significant. The results show that the IVOL effect is robust to controlling for MAX or MIN.

We also perform the reverse sort, i.e., examine the explanatory power of MAX and MIN after controlling for IVOL. To be specific, we first sort the stocks into quintiles by IVOL, and then within each quintile, we sort stocks into quintiles based on MAX or MIN. Panel B of Table 8 reports the average returns across the five equal-weighted and value-weighted IVOL portfolios to produce quintiles with dispersion in MAX or MIN but with similar levels of IVOL. The results show that once we control for IVOL, the MAX effect becomes insignificant. While the relation between MIN and future stock returns remains mostly insignificant, the sign becomes mostly positive.

We further examine the relations between IVOL and MAX or MIN at the firm level by performing the following Fama and MacBeth (1973) regressions:

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{1,t} MAX_{i,t} + \varepsilon_{i,t+1} \tag{13}$$

Table 8
Returns on portfolios sorted by IVOL (MAX or MIN) controlling for MAX and MIN (IVOL).

Panel A: Sorted by IVOL controlling for MAX and MIN.

Quintile	MAX		MIN	
	EW	VW	EW	VW
Q1(Low IVOL)	1.91	1.09	2.05	1.08
2	1.66	1.05	1.88	1.42
3	1.45	1.13	1.55	1.10
4	1.27	1.18	1.17	0.93
Q5(High IVOL)	0.83	0.70	0.48	0.51
Return difference	−1.08	−0.39	−1.57	−0.57
	(−6.39)	(−1.43)	(−9.06)	(−2.13)
Alpha difference	−1.04	−0.52	−1.59	−0.74
	(−6.90)	(−2.31)	(−8.65)	(−2.44)

Panel B: Sorted by MAX or MIN controlling for IVOL

Quintile	IVOL		Quintile	IVOL	
	EW	VW		EW	VW
Q1(Low MAX)	1.38	0.82	1(Low MIN)	1.27	1.06
2	1.48	1.28	2	1.34	1.11
3	1.44	1.12	3	1.47	1.23
4	1.48	1.11	4	1.58	1.23
Q5(High MAX)	1.35	1.01	5(High MIN)	1.73	1.28
Return difference	−0.03	0.19	Return difference	0.46	0.21
	(−0.18)	(0.71)		(1.97)	(0.68)
Alpha difference	−0.17	−0.12	Alpha difference	0.25	−0.32
	(−1.21)	(−0.50)		(1.60)	(−1.28)

Notes: In Panel A, we first sort the stocks into quintiles by maximum/minimum daily return (MAX/MIN), and then within each quintile, we sort stocks into quintiles based on idiosyncratic volatility (IVOL). In Panel B, we first sort the stocks into quintiles by idiosyncratic volatility (IVOL), and then within each quintile, we sort stocks into quintiles based on maximum/minimum daily return (MAX/MIN). The double-sorted, equal-weighted and value-weighted quintile portfolios are formed every month from January 1997 to December 2014. This table presents average returns across the five control portfolios to produce quintiles with dispersion in the variable of interest but with similar levels of the control variable. ''Return difference'' and ''Alpha difference'' are the differences in average raw returns and FF-4 alphas on the high MAX or MIN and low MAX or MIN portfolios. The corresponding West and Newey (1987) t-statistics are reported in parentheses.

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{1,t} MAX_{i,t} + \sum \beta_{j,t} Control_{i,t} + \varepsilon_{i,t+1} \quad (14)$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{2,t} MIN_{i,t} + \varepsilon_{i,t+1} \quad (15)$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{2,t} MIN_{i,t} + \sum \beta_{j,t} Control_{i,t} + \varepsilon_{i,t+1} \quad (16)$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{1,t} MAX_{i,t} + \gamma_{2,t} MIN_{i,t} + \varepsilon_{i,t+1} \quad (17)$$

$$R_{i,t+1} = \alpha_t + \gamma_{0,t} IVOL_{i,t} + \gamma_{1,t} MAX_{i,t} + \gamma_{2,t} MIN_{i,t} + \sum \beta_{j,t} Control_{i,t} + \varepsilon_{i,t+1} \quad (18)$$

The results are reported in Table 9. When we add IVOL to the regressions, the average slope of MAX becomes insignificant, i.e., −0.037 (t-stat = −1.47) and −0.025 (t-stat = −1.61) in specifications (1) and (2) of Table 9, respectively. The negative MIN-return relation is reversed when IVOL is included in the regressions, i.e., 0.083 (t-stat = 1.73) and 0.058 (t-stat = 1.84) in specifications (3) and (4) of Table 9, respectively. However, the average slope of IVOL remains negative and significant at all conventional levels in all the specifications. We perform robustness checks to ensure that the results are not driven by potential outliers. We re-run the cross-sectional regressions by winsorizing IVOL, MAX and MIN at the 99th and 95th percentiles to mitigate the effect of outliers and confirm that the results are consistent. As shown in Table 1, IVOL, MAX and MIN are positively correlated. To provide an intuition of why IVOL subsumes the predictive power of MAX and MIN for stock returns, we also computed the correlation between IVOL and future stock returns. Over our sample period, the average correlation between IVOL and future stock returns is −0.042 with a standard error of 0.006. Compared to the average correlation between MAX and future stock returns (−0.031 with a standard error of 0.006) and the average correlation between MIN and future stock returns (−0.006 with standard error of 0.008), IVOL has the strongest relation with future stock returns, and as such, it subsumes the predictive power of MAX and MIN for stock returns.

In contrast with empirical findings in the literature, we find that while there is a significant MAX effect in the Chinese stock market, it does not subsume the IVOL anomaly. Instead, the MAX effect is subsumed by the IVOL anomaly. Additional analysis based on extreme negative returns (MIN) shows that the IVOL anomaly reverses the MIN effect in the Chinese stock market. Our empirical findings suggest that the IVOL anomaly in the Chinese stock market is beyond the effect of typical investor behavioral biases.

Table 9
Firm-level cross-sectional return regressions on IVOL, MAX and MIN.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.029***	0.044*	0.023***	0.042	0.025***	0.040
	(3.57)	(1.66)	(3.15)	(1.61)	(3.44)	(1.56)
IVOL	−0.785***	−0.840***	−0.958***	−0.983***	−0.940***	−0.946***
	(−6.60)	(−10.09)	(−10.58)	(−12.60)	(−8.52)	(−11.36)
MAX	−0.037	−0.025			−0.026	−0.017
	(−1.47)	(−1.61)			(−1.13)	(−1.13)
MIN			0.083*	0.058*	0.082*	0.055*
			(1.73)	(1.84)	(1.77)	(1.76)
SIZE		−0.002		−0.002		−0.002
		(−1.18)		(−1.18)		(−1.11)
BETA		0.005***		0.003***		0.004***
		(5.04)		(3.95)		(4.81)
BM		0.007*		0.007*		0.008*
		(1.78)		(1.79)		(1.83)
REV		−0.001		−0.000		−0.001
		(−0.12)		(−0.01)		(−0.16)
MOM		0.009***		0.009***		0.009***
		(2.91)		(2.89)		(2.95)
ILLIQ		0.020***		0.019***		0.019***
		(4.39)		(4.27)		(4.22)
ISKEW		−0.147**		−0.144**		−0.143**
		(−2.43)		(−2.37)		(−2.35)
COSKEW		0.004		0.005		0.005
		(0.22)		(0.28)		(0.30)
Adj. R^2	2.52%	11.19%	3.51%	11.36%	4.11%	11.64%

Notes: Each month, we run firm-level cross-sectional regressions of stock returns on lagged predictor variables including idiosyncratic volatility (IVOL), maximum/minimum daily return in the previous month (MAX/MIN), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). This table reports the time-series averages of the cross-sectional regression coefficients, their associated West and Newey (1987) t-statistics (in parentheses), and adjusted R^2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1997 to December 2014.

3.4. Robustness check: alternative measures of MAX and MIN

It is both simple and intuitive to use the single day with the maximum (minimum) return as a proxy for extreme positive (negative) returns. Bali et al. (2011) document – for the U.S. equity market – that the MAX effect stands up very well when MAX is defined as the average of the highest returns within one month using up to five daily return observations. In this section, we further check the robustness of our findings on the relations between IVOL anomaly and the MAX and MIN effects in the Chinese stock market using alternative measures. MAXN (MINN) is defined as the average of the N highest (lowest) daily returns over the previous month (N = 2, 3, 4, 5). In the interest of brevity, we do not report detailed results of all the alternative measures of MAX and MIN, but they are available from the authors upon request. We observe that measuring extreme positive (negative) returns using multiple day averages does not change our general findings. The results are qualitatively similar, and thus lead to the same inferences.

Table 10 presents the results employing MAX5 as the measure of extreme positive return and MIN5 as the extreme negative return. First, as shown in specifications (1)–(5) of Table 10, there is a strong MAX effect as well as MIN effect in the Chinese stock market. The average coefficient of MIN5 becomes insignificant when MAX5 is added to the regression (specification (5) of Table 10). We perform robustness checks to ensure that the results are not driven by potential outliers. We re-run the cross-sectional regressions by winsorizing MAX5 and MIN5 at the 99th and 95th percentiles to mitigate the effect of outliers, and the results are consistent. As shown in Table 1, MAX5 and MIN5 are positively correlated. To provide an intuition of why MAX5 subsumes the predictive power of MIN5 for stock returns, we also computed the correlation between MAX5 and future stock returns and the correlation between MIN5 and future stock returns. Over our sample period, the average correlation between MAX5 and future stock returns is −0.039 with a standard error of 0.008, and the average correlation between MIN5 and future stock returns is −0.016 with standard error of 0.010. That is MAX5 has a stronger relation with future stock returns, and as such, it subsumes the predictive power of MIN5 for stock returns.

Second, as shown in specifications (6)–(8) of Table 10, the IVOL anomaly is not subsumed by the MAX or MIN effect. The coefficient of MAX5 remains significant with IVOL but becomes insignificant when MIN5 is also included whereas the coefficient of MIN5 turns positive but is insignificant (specifications (7) and (8) of Table 10). We perform robustness checks to ensure that the results are not driven by potential outliers. We re-run the cross-sectional regressions by winsorizing IVOL, MAX5 and MIN5 at the 99th and 95th percentiles to mitigate the effect of outliers, and the results are consistent. Different from MAX which becomes insignificant when IVOL is controlled for, MAX5 remains weakly significant (at 10% level) even when IVOL is controlled for. The correlation between MAX5 and future stock returns (i.e., −0.039 with a standard error of 0.008) is slightly stronger than the correlation between MAX and future stock returns (i.e., −0.031 with a standard error of 0.006). This potentially explains why MAX5 remains weakly significant after controlling for IVOL. Also different from MIN which reverses to positive sign and becomes significant when IVOL is controlled for, MIN5 reverses to positive sign but insignificant when IVOL controlled for. That is, given the same level of IVOL, the relation between MIN5 and future stock returns is positive but insignificant. This is consistent with the observation that MIN5 has a slightly stronger negative relation with

Table 10
Firm-level cross-sectional return regressions on IVOL, MAX5 and MIN5.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.027***	0.039	0.010	0.035	0.035	0.047*	0.037	0.038
	(3.69)	(1.49)	(1.43)	(1.35)	(1.37)	(1.81)	(1.44)	(1.48)
IVOL						−0.804***	−0.975***	−0.903***
						(−8.55)	(−10.46)	(−8.38)
MAX5	−0.366***	−0.491***			−0.466***	−0.118*		−0.100
	(−7.08)	(−10.26)			(−8.99)	(−1.87)		(−1.53)
MIN5			−0.293***	−0.320***	−0.097		0.082	0.097
			(−3.83)	(−3.90)	(−1.10)		(0.85)	(1.02)
SIZE		−0.002		−0.002	−0.002	−0.002	−0.002	−0.002
		(−1.03)		(−1.31)	(−0.94)	(−1.23)	(−1.06)	(−1.01)
BETA		0.005***		0.004***	0.005***	0.005***	0.003***	0.003***
		(6.06)		(4.82)	(6.36)	(5.18)	(3.50)	(4.60)
BM		0.009**		0.010**	0.009**	0.007*	0.008*	0.008*
		(2.14)		(2.32)	(2.27)	(1.83)	(1.84)	(1.89)
REV		−0.009		−0.005	−0.006	−0.003	0.001	−0.002
		(−1.50)		(−0.85)	(−0.90)	(−0.41)	(0.22)	(−0.24)
MOM		0.007**		0.007**	0.007**	0.008***	0.009***	0.008***
		(2.29)		(2.15)	(2.34)	(2.77)	(2.86)	(2.76)
ILLIQ		0.022***		0.011**	0.020***	0.019***	0.018***	0.019***
		(4.37)		(2.60)	(4.07)	(3.97)	(4.40)	(3.96)
ISKEW		−0.144**		−0.147**	−0.141**	−0.146**	−0.150**	−0.140**
		(−2.38)		(−2.38)	(−2.35)	(−2.44)	(−2.44)	(−2.40)
COSKEW		0.000		0.008	0.001	0.001	0.006	0.003
		(0.03)		(0.50)	(0.10)	(0.07)	(0.38)	(0.27)
Adj. R^2	1.81%	10.91%	1.79%	10.91%	11.89%	11.41%	11.82%	12.33%

Notes: Each month, we run firm-level cross-sectional regressions of stock returns on lagged predictor variables including idiosyncratic volatility (IVOL), the average of five highest/lowest daily returns over the previous month (MAX5/MIN5), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). This table reports the time-series averages of the cross-sectional regression coefficients, their associated West and Newey (1987) t-statistics (in parentheses), and adjusted R^2. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1997 to December 2014.

future stock returns (i.e., −0.016 with standard error of 0.010) than MIN (i.e., −0.006 with standard error of 0.008). Since IVOL has the strongest relation with future stock returns, it largely subsumes the predictive power of MAX5 and MIN5 for stock returns.

In summary, the results based on alternative measure of MAX and MIN confirm our main findings on the MAX and MIN effects in the Chinese stock market. Moreover, they corroborate that the IVOL anomaly is not subsumed by the MAX or MIN effect. That is to say, the IVOL anomaly is not driven by investor behavioral biases in the Chinese stock market. Instead, the MAX or MIN effect is largely subsumed by the IVOL effect.

4. Further analysis: IVOL anomaly, MAX and MIN effects, and investor sentiment

Baker and Wurgler (2006) construct a market-wide sentiment index (known as BW sentiment index) and provide evidence that investor sentiment affects the cross-section of stock returns, and high sentiment is a significant predictor of the returns of more speculative stocks such as small, young, highly volatile firms. Stambaugh, Yu, and Yuan (2012) find that many asset pricing anomalies are stronger in periods of high sentiment. Corredor, Ferrer, and Santamaria (2013) show that sentiment has a significant influence on stock returns. Recently, Fong and Toh (2014) show that the MAX effect only exists following high investor sentiment state. In this section, we further examine the IVOL anomaly, the MAX effect, the MIN effect and the relation between IVOL and MAX or MIN during sub-sample periods with high and low investor sentiment in the Chinese stock market. Since there is no sufficient information to replicate the BW sentiment index in China, we follow Stambaugh et al. (2012) and use Consumer Confidence Index (CCI) to proxy for investor sentiment in the Chinese stock market. A high (low) sentiment period is defined as one in which the CCI is above (below) the sample median value.

The Fama-MacBeth regression results in high and low investor sentiment states are reported in Table 11. The negative IVOL-return relation is significant at all conventional levels in both high and low investor sentiment states. The average slope of IVOL is −0.754 with a t-statistic of −7.23 in high investor sentiment state and is −0.939 with a t-statistic of −9.07 in low investor sentiment state. We find significant MAX effect in both high and low investor sentiment states in the Chinese stock market. The average slope of MAX is −0.130 with a t-statistic of −6.57 in high investor sentiment state and is −0.160 with a t-statistic of −7.00 in low investor sentiment state. This is different from Fong and Toh (2014) who find that the MAX effect exists only in high investor sentiment state in the U.S. stock market. The MIN effect also exists in both sentiment states. The average slope of MIN is −0.113 (t-stat = −2.68) and −0.099 (t-stat = −2.15) in high and low investor sentiment states, respectively. Consistent with full sample results, Table 11 shows that the average slope of MAX becomes insignificant in both states once IVOL is added, indicating that MAX effect is subsumed by IVOL effect in both high and low sentiment states. The average slope of MIN turns positive in both states, but is significant in low investor sentiment state. That is, given the same level of IVOL, stocks with extreme negative daily return have higher returns next month in the low sentiment state. This is consistent with the pattern documented in Bali et al. (2011) for the U.S. market. We interpret the finding as evidence that during low sentiment period investors exhibit a weaker tendency of chasing stocks with extreme negative returns. Hence, these stocks subsequently have higher returns.

Table 11
Firm-level cross-sectional return regressions in high and low sentiment states.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A High sentiment state.							
Intercept	0.015	0.011	0.014	0.004	0.012	0.014	0.011
	(0.37)	(0.26)	(0.35)	(0.10)	(0.30)	(0.34)	(0.29)
IVOL	−0.754***				−0.706***	−0.800***	−0.760***
	(−7.23)				(−5.77)	(−7.15)	(−6.04)
MAX		−0.130***		−0.099***	−0.017		−0.015
		(−6.57)		(−5.20)	(−0.86)		(−0.79)
MIN			−0.113***	−0.074*		0.012	0.013
			(−2.68)	(−1.78)		(0.28)	(0.31)
Control variables	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	11.55%	11.04%	11.06%	11.92%	11.90%	12.12%	12.43%
Panel B Low sentiment state.							
Intercept	0.079**	0.052	0.054	0.059*	0.075**	0.072**	0.070**
	(2.32)	(1.30)	(1.44)	(1.76)	(2.21)	(2.15)	(2.10)
IVOL	−0.939***				−0.826***	−1.053***	−0.986***
	(−9.07)				(−7.02)	(−10.02)	(−8.45)
MAX		−0.160***		−0.130***	−0.037		−0.022
		(−7.00)		(−7.21)	(−1.62)		(−0.95)
MIN			−0.099**	−0.027		0.107**	0.095**
			(−2.15)	(−0.64)		(2.50)	(2.27)
Control variables	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	9.10%	9.04%	8.61%	9.39%	9.47%	9.57%	9.90%

Notes: Each, we run firm-level cross-sectional regressions of monthly stock returns on lagged predictor variables including idiosyncratic volatility (IVOL), maximum/minimum daily return in the previous month (MAX/MIN), firm size (SIZE), market beta (BETA), book-to-market ratio (BM), short-term reversal (REV), momentum (MOM), illiquidity (ILLIQ), idiosyncratic skewness (ISKEW), and co-skewness (COSKEW). Panel A (B) reports the time-series averages of the cross-sectional regression coefficients, their associated West and Newey (1987) t-statistics (in parentheses), and adjusted R^2 in high (low) sentiment state. A month is classified as high (low) sentiment state if the Consumer Confidence Index (CCI) during that month is above (below) the median value over the sample period. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1997 to December 2014.

5. Conclusion

In this paper, we first document the return predictability of idiosyncratic volatility, the maximum daily return (MAX), and the minimum daily return (MIN) in the Chinese stock market. Second and more importantly, we investigate whether the IVOL anomaly is driven by the MAX or MIN effect in the Chinese stock market. In contrast with Bali et al. (2011), we find that while there is a significant MAX effect in the Chinese stock market, it does not reverse the IVOL effect. Instead, our results show that the IVOL effect actually subsumes the MAX effect in the Chinese market. Additional analysis based on extreme negative returns (MIN) also shows that the IVOL effect reverses the MIN effect in the Chinese stock market.

The findings based on the Chinese stock market, a much larger and yet unique emerging market, are interesting and warrant an explanation. First of all, consistent with the observation that the Chinese stock market is dominated by individual investors, we find evidence that investors do exhibit strong preference for lottery-like stocks and tendency to chase stocks with extreme negative returns. Second, different from the developed U.S. and European stock markets and relatively more advanced South Korea market, the Chinese stock market remains at its preliminary development stage. There are stronger market frictions associated with unique institutional setting in the Chinese stock market, such as daily price limits, short-sale restriction, higher level of information asymmetry, etc. Such market frictions present clear limits to arbitrage for sophisticated investors to arbitrage away mispricing in the Chinese stock market. Our finding that the IVOL effect cannot be explained by investor behavioral biases seems to suggest that market frictions and limits to arbitrage play even more important roles in driving anomalous stock returns in the Chinese stock market. The finding also corroborates the argument in Carpenter et al. (2015) that while the Chinese investors exhibit typical behavior biases, “China's stock market no longer deserves its reputation as a casino.”

Acknowledgements

I would like to thank the Editor Professor Carl R. Chen and an anonymous reviewer for comments and suggestions that have helped to significantly improve the paper. I also gratefully acknowledge helpful comments and suggestions from Xin Chen, Liang Dai, Chun-Yu Ho, Kewei Hou, Nan Li, Manapon Limkriangkrai, Weishu Liu, Hidenori Takahashi, Chaojun Yang as well as seminar participants at Shanghai Jiao Tong University and the 28th Asian Finance Association Annual Meeting. All errors are my own responsibility.

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