論 説

An Empirical Study on the "Idiosyncratic Volatility Puzzle" from the Perspective of Prospect Theory

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Abstract

A negative correlation between idiosyncratic volatility and expected stock return is widely confirmed in many countries' stock markets, and there are various explanations for this phenomenon. From the approach of prospect theory, this paper analyzes the impact of unrealized capital gains on the correlation between idiosyncratic volatility and expected stock return in the Chinese stock market. The paper finds that the negative correlation between idiosyncratic volatility and expected stock return is concentrated on unrealized capital losses. Through regression analysis, the present research finds that prospect theory plays a significant role in explaining this negative correlation. Moreover, the "idiosyncratic volatility puzzle" does not exist in January in the Chinese stock market.

Key words: Idiosyncratic volatility puzzle; Prospect theory; Maximum daily return; January effect

1. Introduction

According to the traditional capital asset pricing model (CAPM), under the assumptions of a highly efficient market and rational investors, a stock's expected return is related only to systemic risks. By contrast, non-systemic risks (i.e., idiosyncratic risks) at both the company and industry levels can be avoided through diversified investment. However, in practice, investors usually cannot avoid non-systemic risks by fully diversifying their investments. Under such circumstances, Merton (1987) believed that stocks with a higher level of idiosyncratic risk should receive higher returns.

However, the phenomenon that demonstrates the negative correlation between idiosyncratic volatility and expected returns has been widely confirmed in the literature. Ang et

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al. (2006) took the residual standard deviation of a regression using the Fama-French three-factor model for idiosyncratic volatility and discovered a significant negative correlation between idiosyncratic volatility and expected stock returns. This phenomenon is known as the "idiosyncratic volatility puzzle." Yang and Han (2009) used the same method to prove that a negative correlation also exists between idiosyncratic volatility and expected returns on the Chinese stock market. However, other scholars believe that the reason why the idiosyncratic volatility puzzle exists is because realized idiosyncratic volatility is regarded as expected idiosyncratic volatility. Fu (2009) used the EGARCH model to infer the expected idiosyncratic volatility and positively correlated it with expected returns. Deng and Zheng (2011) used an autoregressive moving average (ARMA) model to calculate idiosyncratic volatility and found a positive correlation between it and expected returns.

The idiosyncratic volatility puzzle has been explained from various perspectives. Huang et al. (2010) noted that the short-term return reversal effect might explain it. Bali et al. (2011) confirmed that the maximum daily return of one month might explain the negative correlation between idiosyncratic volatility and expected return. Liu et al. (2014) proved that under the combined action of the stock price range, maximum daily returns, and turnover, the negative correlation between idiosyncratic volatility and expected stock returns was no longer significant.

Bhootra and Hur (2015) explained the negative correlation between idiosyncratic volatility and expected stock returns using prospect theory. They confirmed that this negative correlation is concentrated on unrealized capital losses but does not exist in unrealized capital gains. This result is robust even after controlling for maximum daily returns and short-term return reversals. Egginton and Hur (2018) further verified the MAX effect documented by Bali (2011) and the idiosyncratic volatility puzzle. According to the disposition effect and anchoring bias, stocks were divided into two categories: overpriced and underpriced. They established that after controlling for maximum daily returns, the idiosyncratic volatility puzzle was no longer robust. Moreover, the MAX effect only existed for overpriced stocks with unrealized capital losses. Lee and Li (2016) verified the correlation between idiosyncratic volatility and expected stock returns by applying prospect theory using a return quantile regression. They found that in higher quantiles, idiosyncratic volatility and expected stock return was positively related, while in lower quantiles, the correlation was negative. This means that investors are less willing to gamble when they lose and more willing to gamble when they gain, which is consistent with prospect theory. Xie (2017) confirmed a negative correlation between idiosyncratic volatility and expected stock return on the Chinese stock market. Using Bhootra and Hur's (2015) method, they discovered that the negative correlation was further strengthened with capital gains, illustrating that unrealized capital gains did, in fact, influence the correlation between idiosyncratic volatility and expected stock return.

The present study re-verifies the correlation between idiosyncratic volatility and expected stock return on the Chinese stock market. Then, the capital gains overhang is quantified using Grinblatt and Han's (2005) method. According to Bhootra and Hur's (2015) analytical method, the samples were formed according to the stocks' capital gains overhangs, and the correlation between idiosyncratic volatility and expected stock return is explained from the perspective of prospect theory. The present study then investigates whether this result was still significant after controlling for maximum daily returns. The idiosyncratic volatility puzzle is also examined using the January effect.

The analysis results are as follows. First, it was observed that idiosyncratic volatility was positively related to expected stock returns in the Chinese stock market during the time period of analysis. That is, no idiosyncratic volatility puzzle was observed in the Chinese market. Secondly, by classifying the capital gains overhang, it was confirmed that the negative correlation between idiosyncratic volatility and expected returns existed in the groups with the highest capital gains and lowest capital losses. The negative correlation was more obvious in the group with the highest capital losses after controlling the max daily return. Finally, according to the Fama-Macbeth cross-sectional regression analysis results, the "idiosyncratic volatility puzzle" was only observed in the CL1 sub-group after controlling for the daily maximum return, the logarithm of market value and the book-to-market ratio. Furthermore, consistent with the work of Peterson and Smedema (2011), no "idiosyncratic volatility puzzle" was observed in the month of January in the Chinese stock market.

After previous studies of the Chinese stock market, the present study is a new attempt to highlight the existence of the "idiosyncratic volatility puzzle" and demonstrate that the negative correlation between idiosyncratic volatility and expected stock return is concentrated on unrealized capital losses in Chinese stock market.

As opposed to previous studies, this is the first paper to analyze the correlation between idiosyncratic volatility and expected returns in the Chinese market after controlling for maximum daily returns. In addition, the present study also verifies the particularity of the correlation between idiosyncratic volatility and expected returns in January by combining the analysis with the January effect.

2. Data and Methodology

In the present study, all selected stocks were listed on the China A-share market between January 1, 2000 and December 31, 2016, and all data used were sourced from the China Stock Market and Accounting Research Database. Stocks that traded for less than

15 days per month were excluded from the calculations to ensure that sufficient data were available to conduct a regression to measure idiosyncratic volatility. To prevent the impact of outliers, all continuous variables were winsorized at the 1% and 99% levels.

2.1 Estimation of idiosyncratic volatility

Following Ang et al. (2006), the Fama-French three-factor model's residual standard deviation is used as the monthly idiosyncratic volatility of stocks. First, the daily data of each stock are regressed to Equation (1), so that a residual is obtained for each stock each month. The result multiplied by the residual standard deviation and the square root of the number of trading days each month is taken as the monthly idiosyncratic volatility (IVOL) of the stock.

$$r_{i,d}-r_{f,d}=\alpha_i+\beta_i(r_{m,d}-r_{f,d})+\gamma_i SMB_d+\varphi_i HML_d+\varepsilon_{i,d} \quad (1)$$

$$IVOL_{i,t}=\sqrt{n_{i,t}}\,Std(\varepsilon_{i,t}) \quad (2)$$

where $r_{i,d}$ is the return of stock i on day d, $r_{f,d}$ is the risk-free rate on day d, $r_{m,d}$ is the return of market on day d, SMB_d and HML_d are the size factor and bm ratio factor respectively, and n is the trading days of stock i in the month.

2.2 Estimation of the Capital Gains Overhang

According to the S-shaped utility function that corresponds to prospect theory as proposed by Kahneman and Tversky (1979) (Figure 1), investors set reference points when making decisions. The S-shaped utility function illustrates that people tend to be risk-averse in the domain of gains (concave) but risk-seeking in the domain of losses (convex). For the idiosyncratic volatility puzzle, it could be concluded that, in the domain of losses, investors prefer stocks with high idiosyncratic volatility, which leads to their overvaluation and lower expected returns. When it comes to the domain of gains, investors prefer stocks with low idiosyncratic volatility to avoid risk, causing them to become undervalued and thus obtaining higher expected returns. However, Bhootra and Hur (2015) assumed that the correlation between idiosyncratic risk and expected return was uncertain in the domain of gains. It is also feasible that risk-averse investors could eliminate diversification risks using the traditional CAPM. Therefore, they assumed that the negative correlation between idiosyncratic volatility and expected return only exists for stocks with unrealized gains.

In the present study, Grinblatt and Han (2005) method is used to represent the capital gain overhang (CGO) as the percentage deviation between the stock price (P) and the current reference price (RP), using the cost of acquiring the stock as the reference price. If CGO is positive, it would be denoted as CG (capital gains); on the contrary, if CGO is

Figure 1 S-shaped Utility Function

Figure 1 depicts S-shape utility function:

$$u(x)=x^{\alpha},\ x\geq 0\ (0<\alpha<1)$$

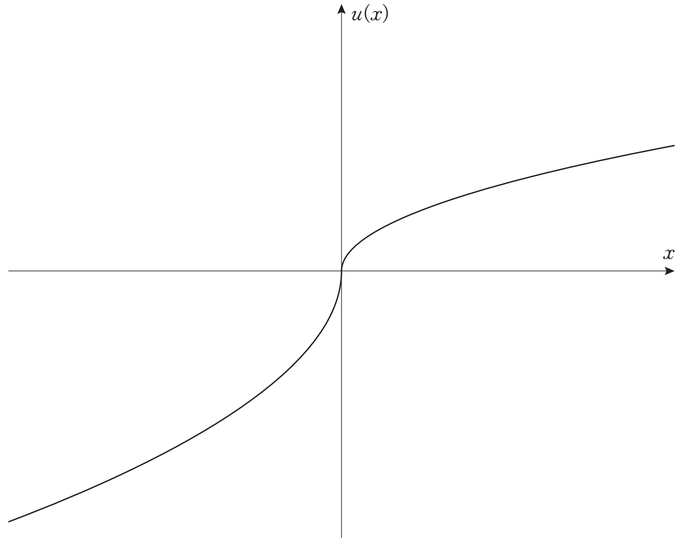
$$u(x)=-\lambda(-x)^{\beta},\ x<0\ (0<\beta<1,\ \lambda>1),$$

The S-shaped utility is the same as that of Bhootra and Hur (2015), generated by

$$u(x)=x^{0.5},\ x\geq 0$$

$$u(x)=-2(-x)^{0.5},\ x<0$$

Prospect Theory Utility Fuction



negative, it would be denoted as CL (capital losses).

$$CGO_{i,t}=(P_{i,t}-RP_{i,t})/P_{i,t} \quad (3)$$

where $CGO_{i,t}$ is the capital gains overhang of stock i at the end of the month t, and $P_{i,t}$ is the price of stock i in the month t, $RP_{i,t}$ is the reference price of stock i at the end of month t.

The reference price is estimated through the stock daily closing price in the past three years and the daily turnover rate as the weight following the Equation (4),

$$RP_{i,t}=\frac{1}{k}\sum_{n=1}^{T}(V_{i,t-n}\prod_{\tau=1}^{n-1}[1-V_{i,t-n+\tau}])P_{i,t-n} \quad (4)$$

where T is the number of stock trading days in the past three years, $V_{i,t-n}$ is the turnover rate of stock i on the day t−n, $P_{i,t-n}$ is the closing price of stock i on the day t−n, and the k is the constant that makes the weight sum up to one. The measurable period is taken from January 2003 to December 2016.

Table 1 is the summary statistics of the present study, where Ri is the monthly stock return; IVOL is the idiosyncratic volatility of stocks; CGO is the capital gains overhang,

Table 1 Summary Statistics 2003-2016

This table represents descriptive statistics for the variable. Ri is the monthly stock return. IVOL is the idiosyncratic volatility of stocks. CGO is the capital gains overhang, estimated by $CGO_{i,t}=(P_{i,t}-RP_{i,t})/P_{i,t}$. MAX is the stock maximum daily return. MV is the market value. BM is the book-to-market ratio. Panel A is the data of the full period, and panel B is that without January.

variable	obs	mean	sd	min	max
Panel A Full Period					
Ri	210243	0.0191	0.1458	−0.7819	1.8945
IVOL	229734	0.0823	0.0400	0.0023	1.1062
CGO	229734	0.8978	0.2518	−0.7794	0.9998
MAX	229734	0.0559	0.0276	0.0000	1.2612
MV	229734	8.34E+09	4.41E+10	2.50E+07	2.17E+12
BM	229612	0.9146	1.3093	−36.7352	91.2605
Panel B Non-January					
Ri	193777	0.0143	0.1480	−0.7819	1.8945
IVOL	213238	0.0824	0.0400	0.0023	1.1062
CGO	213238	0.8972	0.2528	−0.7794	0.9998
MAX	213238	0.0559	0.0278	0.0000	1.2612
MV	213238	8.40E+09	4.41E+10	2.50E+07	2.17E+12
BM	213116	0.9135	1.3120	−36.7352	91.2605

which is estimated by $CGO_{i,t}=(P_{i,t}-RP_{i,t})/P_{i,t}$; MAX is the stock maximum daily return; MV is the market value, and BM is the book-to-market ratio. Panel A is the data of the full period, and panel B is that without January.

3. An Empirical Analysis of Capital Gains Overhang and Idiosyncratic Volatility Puzzle

3.1 Reexamination of the Idiosyncratic Volatility and Stock Return

First of all, to reexamine the correlation between the idiosyncratic volatility and the stock expected return in the Chinese stock market, the analysis objects are divided into quintile portfolios based on the idiosyncratic volatility (IVOL) each month, and the value-weighted return of each factor is examined. The null hypothesis is that the difference in the value-weighted expected return of portfolio 5 to portfolio 1 is equal to zero. The details of the portfolio analysis are reported in Table 2.

Table 2 shows that higher idiosyncratic volatility led to a higher value-weighted return. Moreover, the difference in the monthly value-weighted return between portfolio 5 and portfolio 1 is positive and achieves at a significance level of 1% (0.0073, *t*-statistic: 6.70). Therefore, consistent with chapter 2. Table 2 reexamines that no idiosyncratic volatility

Table 2 Portfolios Sorted by Idiosyncratic Volatility

This table reports the quintile portfolios by sorting stocks based on the idiosyncratic volatility each months. For each portfolio, IVOLS is the short-term idiosyncratic volatility, VW RETRUN is the monthly value weighted return of stock i, "5-1" is the difference between portfolio 5 and portfolio 1. The numbers in brackets are t values. *, ** and *** respectively mean significant at the significance level of 10%, 5%, and 1%.

Rank	IVOL	VW RETRUN
1 low	0.0457	0.0227
2	0.0637	0.0320
3	0.0790	0.0294
4	0.0977	0.0297
5 high	0.1369	0.0300
5-1	0.0912	0.0073
t	[479.74]***	[6.70]***

puzzle is observed in the Chinese stock market.

3.2 Idiosyncratic Volatility Puzzle and Capital Gains Overhang

Bhootra and Hur (2015) examined the negative correlation between idiosyncratic volatility and expected stock return using prospect theory. They divided the objects sorting by idiosyncratic volatility and capital gains overhang. They confirmed that the negative correlation between idiosyncratic volatility and expected stock return is concentrated on unrealized capital losses but is not observed for unrealized capital gains.

Following the work of Bhootra and Hur (2015), the selected stocks were sorted each month into five sub-groups based on idiosyncratic volatility (IVOL) over the past month. Then, in each IVOL sub-group, four sub-groups were further classified according to capital gains overhang (CGO). If CGO was positive, it would be denoted as CG (capital gains). On the contrary, if CGO was negative, it would be denoted as CL (capital losses). CL1, CL2, CG1, and CG2 were grouped according to the median values of CL and CG. Using the above groupings, 20 portfolios were obtained.

Table 3 reports the value-weighted returns of these sorted portfolios. "5-1" denotes the differential between Portfolio 5 and Portfolio 1, sorted according to IVOL.

Table 3 illustrates that in CL1 and CG2, the value-weighted returns of stocks are lower when IVOL is higher. The difference between the highest and lowest IVOL portfolios for CL1 and CG2, respectively, equal −0.0206 and −0.0413, with *t*-statistics of −4.04 and −12.39. By contrast, the opposite results are shown for CL2 and CG1. In CL2 and CG1, the negative correlation between IVOL and stock returns becomes positive, which indicates that the "idiosyncratic volatility puzzle" is clearly observed in these two groups, namely, CL1 and CG2.

This result is inconsistent with previous research. Bhootra and Hur (2015) found that

Table 3 Portfolios Sorted by IVOL and CGO

This table reports the monthly value-weighted returns for portfolios formed by sorting stocks based on the idiosyncratic volatility and capital gains overhang of the stocks each month. IVOL is the idiosyncratic volatility. If CGO is positive, it would be denoted as CG (capital gains); on the contrary, if CGO is negative, it would be denoted as CL (capital losses). "5-1" is the difference between portfolio five and portfolio one sorted by IVOL. The numbers in brackets are t values. *, ** and *** respectively mean significant at the significance level of 10%, 5%, and 1%.

IVOL	VW RETURN			
	CL		CG	
	CL1	CL2	CG1	CG2
1 low	0.0416	0.0134	0.0299	0.0740
2	−0.0190	0.0306	0.0390	0.0375
3	−0.0209	0.0241	0.0590	0.0394
4	0.0011	0.0238	0.0621	0.0726
5 high	0.0210	0.0381	0.0461	0.0327
5-1	−0.0206	0.0247	0.0162	−0.0413
t	[−4.04]***	[17.16]***	[8.49]***	[−12.39]***

the negative correlation between IVOL and expected returns focused on CL. Xie (2017) showed that there was a negative correlation between IVOL and stock returns for all groups of the Shenzhen A-share market, but it was more evident for CG.

3.3 Portfolio Analysis Controlled by MAX

Bali et al. (2011) considered stocks with a maximum daily return as lottery stocks and highlighted the negative correlation between maximum daily return (MAX) and expected stock returns. This phenomenon is the so-called "MAX effect." Investors' preference for such stocks caused the overvaluation of their earnings, leading to lower expected returns. The research also highlighted that the MAX effect might explain the idiosyncratic volatility puzzle.

To verify whether the MAX effect changed results before, this section reconstructs the portfolios, sorting them according to IVOL and CGO after controlling for MAX. Initially, all stocks were divided into four groups, according to CGO. Secondly, each CGO sub-group was subdivided into five groups according to MAX. Then, each MAX sub-group was further subdivided into five sub-groups sorted by IVOL. The value-weighted returns were calculated across the five MAX sub-groups within each IVOL sub-group. This way, each combination of IVOL contains stocks with both a high MAX and a low MAX, thus controlling for the MAX variable.

Table 4 shows the results after controlling for the MAX variable. In CL1, the difference between Portfolio 5 and Portfolio 1 is negative and significant, consistent with the results listed in Table 3.1. The difference between Portfolio 5 and Portfolio 1 of CG2 is negative, but not significant. The differences in CL2 and CG1 are no longer significantly positive.

Table 4 Portfolios Sorted by IVOL and CGO after Controlling for MAX

This table reports the monthly value-weighted returns for portfolios formed by sorting stocks based on the idiosyncratic volatility and capital gains overhang of the stocks each month. IVOL is the idiosyncratic volatility. If CGO is positive, it would be denoted as CG (capital gains); on the contrary, if CGO is negative, it would be denoted as CL (capital losses). "5-1" is the difference between portfolio five and portfolio one sorted by IVOL. The numbers in brackets are t values. *, ** and *** respectively mean significant at the significance level of 10%, 5%, and 1%.

IVOL	VW RETURN			
	CL		CG	
	CL1	CL2	CG1	CG2
1 low	0.0522	0.0277	0.0567	0.0443
2	−0.0085	0.0075	0.0415	0.0429
3	−0.0016	0.0213	0.0486	0.0562
4	0.0019	0.0245	0.0622	0.0466
5 high	0.0157	0.0220	0.0568	0.0427
5-1	−0.0365	−0.0057	0.0002	−0.0016
t	[−6.26]***	[−3.75]***	[0.08]	[−0.53]

Compared with CL1, in CG2, the MAX effect weakens the negative impact of IVOL toward expected stock return. The results are similar to those of Bhootra and Hur (2015). The negative correlation between IVOL and expected return is concentrated in stocks with unrealized CL.

3.4 Regression Analysis

In this section, several regressions are performed to further verify the impact of CGO on the "idiosyncratic volatility puzzle." The Fama-Mecbeth cross-sectional regressions are conducted in sub-groups sorted according to the CGO. The analysis regression equation is as follows:

$$R_{i,t+1}=\alpha_i+\beta_i\mathrm{IVOL}_t+\theta_i\mathrm{MAX}_t+\gamma_i\ln\mathrm{MV}_t+\delta_i\mathrm{BM}_t+\varepsilon_{i,t} \quad (5)$$

where the dependent variable $R_{i,t+1}$ is the return of stock i in month t+1. The lagged explanation variables computed in month t include IVOL_t which represents the idiosyncratic volatility MAX_t which represents the maximum stock daily return, $\ln\mathrm{MV}_t$ which represents the logarithm of market value and BM_t represents the book-to-market ratio.

The details of the regression analysis are reported in Table 5. The values in parentheses are the *t*-statistics of the regression coefficients. Models 1 and 2 report the regressions for all months. Models 3 and 4 report regressions in January, while Models 5 and 6 report regressions on all months with the exception of January (i.e., February through December). Panel A shows the regression results of sub-group CL1, Panel B shows the regression results of sub-group CL2, Panel C shows the regression results of sub-group CG2, and Panel D shows the regression results of sub-group CG2.

Table 5 Fama-Mecbeth Cross-Sectional Regressions of the Idiosyncratic Volatility Puzzle

This table shows the regression of the idiosyncratic volatility puzzle using the following models:

$$R_{i,t+1}=\alpha_i+\beta_i IVOL_t+\varepsilon_{i,t}$$

$$R_{i,t+1}=\alpha_i+\beta_i IVOL_t+\theta_i MAX_t+\varepsilon_{i,t}$$

$$R_{i,t+1}=\alpha_i+\beta_i IVOL_t+\theta_i MAX_t+\gamma_i \ln MV_t+\delta_i BM_t+\varepsilon_{i,t}$$

where the dependent variable $R_{i,t+1}$ represents the monthly return of stock i in month t+1. The lagged explanatory variables, computed in month t, include $IVOL_t$ (idiosyncratic volatility), MAX_t (maximum daily return of the stocks), $\ln MV_t$ (the logarithm of market value), and BM_t (book-to-market ratio).. The sample covers the period from January 2003 to December 2016. Model 1, 2, 3 report the regressions in all months. Model 4, 5, 6 report the regressions in January. While Model 7, 8, 9 report the regressions on the months with the removal of January (February-December). If CGO is positive, it would be denoted as CG (capital gains); on the contrary, if CGO is negative, it would be denoted as CL (capital losses). Panel A is the regression results of the sub-group CL1, panel B is the regression results of the sub-group CL2, panel C is the regression results of the sub-group CG2, panel D is the regression results of the sub-group CG2. The numbers in brackets are t values. *, ** and *** respectively mean significant at the significance level of 10%, 5%, and 1%.

					Panel A CL1				
	ALL MONTHS			JANUARY			NON-JANUARY		
	1	2	3	4	5	6	7	8	9
IVOL	−0.0037	−0.0079	−0.0178*	−0.0310	−0.0392	−0.0161	−0.0021	−0.0061	−0.0179*
	(−0.51)	(−1.09)	(−1.81)	(−2.42)	(−1.38)	(−1.51)	(−0.28)	(−0.82)	(−1.73)
MAX		−0.0034	0.0057		0.0011	−0.0033		−0.0036	0.0062
		(−0.70)	(0.47)		(0.18)	(−2.01)		(−0.72)	(0.48)
lnMV			0.0064			−0.0686			0.0107
			(0.15)			(−1.99)			(0.24)
BM			0.0169			0.0179			0.0168
			(0.51)			(1.33)			(0.48)
_cons	0.0228*	0.0160	0.0398	0.0640	0.0938	0.0414	0.0205	0.0116	0.0398
	(1.68)	(1.08)	(1.37)	(1.47)	(1.40)	(1.16)	(1.45)	(0.77)	(1.29)
					Panel B CL2				
	ALL MONTHS			JANUARY			NON-JANUARY		
	1	2	3	4	5	6	7	8	9
IVOL	−0.0069	−0.2866	−0.0148	−0.0069	−0.2866	−0.0148	−0.0069	−0.2866	−0.0148
	(−1.02)	(−1.59)	(−0.72)	(−1.02)	(−1.59)	(−0.72)	(−1.02)	(−1.59)	(−0.72)
MAX		−0.1866	−0.0025		−0.1866	−0.0025		−0.1866	−0.0025
		(−1.49)	(−0.12)		(−1.49)	(−0.12)		(−1.49)	(−0.12)
lnMV			−0.0153			−0.0153			−0.0153
			(−0.46)			(−0.46)			(−0.46)
BM			0.0309			0.0309			0.0309
			(0.68)			(0.68)			(0.68)
_cons	0.0201**	0.0797	0.0076	0.0201**	0.0797	0.0076	0.0201**	0.0797	0.0076
	(2.08)	(0.78)	(0.33)	(2.08)	(0.78)	(0.33)	(2.08)	(0.78)	(0.33)
					Panel C CG1				
	ALL MONTHS			JANUARY			NON-JANUARY		
	1	2	3	4	5	6	7	8	9
IVOL	0.0003	−0.0001	0.0000	0.0022	0.0014	0.0006	0.0001	−0.0002	−0.0000
	(0.45)	(−0.16)	(0.02)	(0.95)	(0.87)	(0.37)	(0.17)	(−0.41)	(−0.09)
MAX		−0.0001	−0.0002		0.0006	−0.0009		−0.0002	−0.0001
		(−0.45)	(−0.78)		(0.71)	(−1.56)		(−0.62)	(−0.47)
lnMV			0.0004			0.0025			0.0003
			(0.31)			(0.55)			(0.18)
BM			0.0012			−0.0029			0.0015
			(1.20)			(−1.23)			(1.46)
_cons	0.0267***	0.0264***	0.0265***	0.0864***	0.0865***	0.0867***	0.0218**	0.0215**	0.0216**
	(3.14)	(3.12)	(3.14)	(5.25)	(5.24)	(5.22)	(2.43)	(2.40)	(2.42)
					Panel D CG2				
	ALL MONTHS			JANUARY			NON-JANUARY		
	1	2	3	4	5	6	7	8	9
IVOL	0.0003	0.0005	−0.0001	0.0022	0.0023	0.0005	0.0001	0.0003	−0.0001
	(0.46)	(0.95)	(−0.17)	(1.19)	(1.20)	(0.24)	(0.17)	(0.61)	(−0.30)
MAX		0.0001	−0.0002		−0.0001	−0.0003		0.0001	−0.0002
		(0.32)	(−0.92)		(−0.17)	(−0.38)		(0.37)	(−0.84)
lnMV			0.0039**			0.0063			0.0037**
			(2.20)			(0.70)			(2.07)
BM			−0.0010			−0.0046			−0.0007
			(−0.96)			(−0.66)			(−0.71)
_cons	0.0260***	0.0259***	0.0262***	0.0817***	0.0813***	0.0803***	0.0214**	0.0214**	0.0217**
	(3.07)	(3.07)	(3.10)	(6.38)	(6.36)	(6.16)	(2.38)	(2.38)	(2.42)

Columns 1, 2 (all months) in Panel A indicate that the coefficients of IVOL are negative but not significant. The coefficient on IVOL is −0.0037 (*t*-statistics=−0.51) in Column 1 and −0.0079 (*t*-statistics=−1.09) in Column 2. After controlling for MAX, lnMV and BM, the coefficient of IVOL becomes negative and significant (−0.0178, *t*-statistics=−1.81). For Panel B, the coefficients of IVOL in Column 1, 2, 3 (all months) is negative but not significant. The coefficient on IVOL is −0.0069 (*t*-statistic=−1.02), and in Column 3, after the addition of MAX, lnMV and BM, the coefficient of IVOL is −0.0148 (*t*-statistics =−0.72).

For Columns 1, 2, 3 (all months) in Panels C and D, the coefficients on IVOL are not significantly negative. For Panel C, the coefficients on IVOL are 0.0003 (*t*-statistics=0.45) in Column 1 and 0.0000 (*t*-statistics=0.02) in Column 3. For Panel D, the coefficient on IVOL are 0.0003 (*t*-statistics=0.46) in Column 1 and −0.0001 (*t*-statistics=−0.17) in Column 3.

Therefore, after the addition of MAX, lnMV and BM, the idiosyncratic volatility puzzle could only be observed in CL1 subgroup, which is consistent with the results displayed in Table 4.

Peterson and Smedema (2011) analyzed the specification for the correlation between IVOL and expected return in January. They noted that the “idiosyncratic volatility puzzle” did not exist in January. Bhootra and Hur (2015) also obtained the same results. Therefore, to test whether this phenomenon also exists in the Chinese market, Table 5 also performed regression in January (Columns 4, 5 and 6) and February to December (Column 7, 8 and 9).

In Column 4, 5, and 6, no negative and significant coefficients of IVOL are observed for all sub-periods sorting by CGO. In other words, consistent with the results of Peterson and Smedema (2011), no “idiosyncratic volatility puzzle” was observed in January in the Chinese stock market.

Then regression results in Columns 7, 8 and 9, are similar with to those in Columns 1, 2 and 3. For Panel A, it is indicated that the coefficients of IVOL are negative but not significant. in Column 7 and 8, whereas after the addition of MAX, lnMV and BM, the coefficient of IVOL becomes negative and significant (−0.0179, *t*-statistics=−1.73). In Columns 7, 8 and 9 of Panels B, C, and D, no significantly negative correlation between IVOL and stock expected return is observed.

The results are similar to those of Bhootra and Hur (2015). In their research, the idiosyncratic volatility puzzle is concentrated in the unrealized capital losses.

4. Conclusion

This paper reexamined the correlation between IVOL and expected stock return. It was confirmed that higher IVOL led to higher value-weighted returns. In other words, no "idiosyncratic volatility puzzle" was observed in the Chinese stock market.

The present study further analyzed the correlation between IVOL and expected stock returns by quantifying the CGO from the perspective of prospect theory. Through portfolio analysis, the study confirmed that the negative correlation between IVOL and expected returns exists in the sub-group with the highest unrealized CG and the sub-group with the lowest unrealized CL. This phenomenon is evident in the sub-group with the highest unrealized CG. This differs from the results of Xie (2017), who claimed that the negative correlation between IVOL and expected returns in all unrealized CG groups tended to be further strengthened by an increase in CG. By controlling MAX, the correlation between IVOL and expected returns tended to be more consistent with prospect theory: the negative correlation was concentrated in those stocks with unrealized CL.

According to the results of regression analysis, the "idiosyncratic volatility puzzle" was only observed in the CL1 sub-group after controlling for MAX, lnMV and BM. This finding is similar to the result of Bhootra and Hur (2015). Furthermore, consistent with the work of Peterson and Smedema (2011), no "idiosyncratic volatility puzzle" was observed in January in the Chinese stock market.

This is a new attempt to examine the existence of the "idiosyncratic volatility puzzle" from the perspective of prospect theory and demonstrate that the MAX effect could not explain the existence of the "idiosyncratic volatility puzzle" in the group of stocks with the lowest capital gains overhang in the Chinese stock market.

References

William F. Sharpe. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. Journal of Finance, 1964(19): 425-442.

Merton R. C., A Simple Model of Capital Market Equilibrium with Incomplete Information. Journal of Finance, 1987(42): 483-510.

Ang A., Hodrick R. J., Xing Y. and Zhang X. The Cross-Section of Volatility and Expected Returns. Journal of Finance., 2006(61): 259-299.

Yang Huawei, Han Liyan, 2009, An Empirical Study of the Relationship between the Idiosyncratic Volatility and the Cross-sectional Return, Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition) 22, 6-10. (In Chinese)

Fu Fangjian. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics, 2009(91): 24-37.

Deng Xuechun, Zheng Zhenlong, 2011, Is There an Idiosyncratic Volatility Puzzle in China's Equity Market, Journal of Business Economics 231, 60-75. (In Chinese)

Huang W, Liu Q, Rhee S G, Zhang L. Return Reversals, Idiosyncratic Risk, and Expected Return. Journal of Financial Research, 2010(23): 147-168.

Bali T G, Cakici N, Whitelaw R F. Maxing out: Stock as Lotteries and the Cross-section of Expected Returns. Journal of Financial Economics, 2011(99): 427-446.

Liu Weiqi, Xing Hongwei, Zhang Xindong, 2014, Investment Preference and the Idiosyncratic Volatility Puzzle, Chinese Journal of Management Science 22, 10-20. (In Chinese)

Daniel Kanhneman, Amos Tversky. Prospect Theory: An Analysis of Decision under Risk. Econometrica, 1979(47): 263-291.

Ajay Bhootra, Jungshik Hur. High Idiosyncratic Volatility and Low Returns: A Prospect Theory Explanation. 2015(2): 295-322.

Mark Grinblatt, Bing Han. Prospect Theory, Mental Accounting, and Momentum. Journal of Financial Economics, 2005(78): 311-339.

Xie hong, Research on the Idiosyncratic Volatility Puzzle of Chinese Stock Market Based on Prospect Theory. WuHan Finance, 2017(11): 26-33. (In Chinese)

Fama, Eugene F., James D. MacBeth, Risk Return, and Equilibrium: Empirical Tests. Journal of Political Economy, 1973(81): 607-636.

Peterson, D. R., A. R., Smedema. The Return Impact of Realized and Expected Idiosyncratic Volatility. Journal of Banking and Finance, 2011(35): 2547-2558.