Does idiosyncratic volatility matter?
— Evidence from Chinese Stock Market

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Abstract

Is idiosyncratic volatility priced? The existing literature finds conflicting results on the cross-sectional relation between expected returns and idiosyncratic volatility. This paper examines the relation between idiosyncratic volatility and expected returns in Chinese Stock Market. We find there is a significantly negative relation between idiosyncratic volatility and expected returns, which phenomenon is also called "idiosyncratic volatility puzzle". However, after controlling for size, book-to-market ratio, liquidity, momentum, herding of institutional investors, positive relation between idiosyncratic volatility and expected returns turn to be negative. This result indicates that in Chinese Stock Market, the idiosyncratic volatility puzzle is just an apparent phenomenon.

JEL Classification: G12, G14

Keywords: Idiosyncratic volatility puzzle, Expected returns, Institutional investors' herding

1. Introduction

The capital asset pricing model (CAPM) predicts there exists a positive linear relation between expected returns on securities and their market betas, and idiosyncratic risk should not be priced because it can be eliminated through diversification. However, there are some theoretical evidences predict that idiosyncratic volatility is positively related to the expected stock returns in the cross section. Levy (1978) theoretically proves that when investors with few stocks in his portfolios, idiosyncratic volatility plays an important role in determining equilibrium asset price. Merton (1987) points out investors with incomplete information demand a return compensation for bearing idiosyncratic risk.

Supporting the theoretical results, Malkiel and Xu (2002) confirm that portfolios with higher idiosyncratic volatility have higher average returns, because investors who cannot hold a fully diversified portfolios demand a return compensation. Spiegel and Wang (2006), Chua, Goh and Zhang (2008) and Fu (2009) find positive relation between expected idiosyncratic volatility and expected returns at the firm or portfolio level.

However, in contrast to the existing literature, a recent paper by Ang, Hodrick, Xing and Zhang (2006, AHXZ hereafter) find that stocks with high idiosyncratic volatility in one month relative to the Fama-French three-factor model predict abysmally low average returns in the next month. This finding is contrary to the exsiting literature and is called "idiosyncratic volatility puzzle". For further confirming, Ang, Hodrick, Xing and Zhang (2009) use data of other G7 countries, the negative relation between average return and idiosyncratic volatility also exist.

AHXZ's findings have attracted much attention. Bali and Cakici (2008) uses a different measure to test the robustness of AHXZ's finding. They indicate that after controlling for the data frequency used to estimate idiosyncratic volatility, the weighting schemes used to compute average portfolio returns, the breakpoints utilized to sort stocks into quintile portfolios, and the exclusion of smallest, lowest priced, and least liquid stocks from the sample, the positive cross-section relation between idiosyncratic risk and expected returns disappears. Besides, they emphasis that the idiosyncratic volatility measure obtained from monthly data is a more accurate proxy for the expected future volatility than the idiosyncratic volatility measure obtained from daily data.

Fu (2009) focus on the time-varying property of idiosyncratic volatility and argues that idiosyncratic volatilities which is estimated by AHXZ vary overtime and thus should not fully capture the relation between idiosyncratic risk and expected return. They emphasis that because the existing literature does not capture the time-varying property so that they cannot identify the positive relation between average return and idiosyncratic volatility. Therefore, instead of using the Fama-French model, Fu employs the GARCH model to estimate expected idiosyncratic volatility, and finds they are positively related to expected returns. Following Fu's method, based on international data, Brockman and Schuute (2007) use the EGARCH method to estimate conditional idiosyncratic volatility and confirm the Fu's results.

Other researches offer explanations for the idiosyncratic volatility puzzle. Huang, Liu, Rhee and Zhang (2007) point out that AHXZ's results are driven by monthly stock return reversals. After controlling for the difference in the past-month returns, they cannot find the negative relation between average return and idiosyncratic volatility. Boehme, Danielsen, Kumar and Sorescu (2009) concentrate on the level of investor recognition and short-sale constraints. They find for stocks that have low levels of institutional holdings and for which short-sold is limited, the relation between idiosyncratic volatility and expected returns is positive.

However, Chen and Petkova (2012) decompose aggregate market variance into an average correlation component and an average variance component. They find portfolios with high idiosyncratic volatility relative to Fama-French model have positive loading with respect to innovations in average variance. This difference in the loading, combined with a negative price of risk for average variance, explains the idiosyncratic volatility puzzle.

Evidences about idiosyncratic volatility puzzle in China Stock Markets have conflict results. Using the China Stock Markets data from 1997 to 2007, Chen, Tu and Lin (2009) finds a significant negative relationship between idiosyncratic volatility and the cross-section of expected returns. Besides, after controlling for other factors such as size, book-to-market ratio and momentum etc., the negative relationship still holds. Nartea, Wu and Liu (2013) also document evidence of a negative idiosyncratic volatility effect in China, and suggest it could be driven by investor preference for high idiosyncratic volatility stocks.

However, Deng and Zheng (2011) examines the idiosyncratic volatility puzzle in China's Equity Market based on data from 1997 to 2009 and argues that lagged idiosyncratic volatility is not a good estimate of expected idiosyncratic volatility. Applying ARMA model to calculate the expected idiosyncratic volatility, idiosyncratic volatility puzzle disappears. However, when estimate the idiosyncratic volatility, they use the past one month of daily data.

The purpose of this paper is to clarify the relation between idiosyncratic volatility and expected returns in China Stock Market. We also detects the reason why existing literature about China Stock Market presenting conflicting evidence. Being different from previous studies in China, we adopt monthly return data in calculating the idiosyncratic volatility. As mentioned in Bali and Cakici (2008), idiosyncratic volatility measure obtained from monthly data is a more accurate proxy for the expected future volatility than the idiosyncratic volatility measure obtained from daily data.

Using monthly return, we show the time-series of idiosyncratic volatility calculated using the Fama-French three-factor model is independent, i.e. it is proper to describe the stocks' idiosyncratic volatility process as a random walk. Regression analysis indicates there is a negative relation between idiosyncratic volatility and expected returns. To further confirm the negative relation observed, we control for some variables: size, book-to-market ratio, turnover ratio, previous 12-month average returns, ownership of institutional investors, foreign investors and the states, change of institutional investors' ownership. We find after controlling these variables, negative relation disappeared, which imply the idiosyncratic volatility puzzle in China is just a apparent phenomenon.

The paper is organized as follows. Section 2 describes the method we take to calculate idiosyncratic volatility and its time-series properties. Section 3 summaries data, examines the relation between expected idiosyncratic volatility and expected returns. Section 4 applies herding of institutional and other factors to examine the robustness of the relation between expected idiosyncratic volatility and expected returns. Section 5 concludes the paper.

2. Idiosyncratic volatility and time-series property

2.1 Estimation of idiosyncratic volatility

The data include stocks from Hushen 300 index for the period from January 2000 to December 2009. We use monthly stock returns to generate the idiosyncratic volatility. Monthly returns are obtained from the CSMAR database[1]. Following AHXZ, we first apply Fama-French three-factor (1993) model to estimate idiosyncratic volatility of individual stocks.

For individual stock i, we run the Fama-French three-factor regression as follows,

$$R_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,t}\left(R_{m,t} - r_{f,t}\right) + s_{i,t}SMB_t + h_{i,t}HML_t + \varepsilon_{i,t} \tag{1}$$

[1] CSMAR® China Stock Market Trading Database.

where $R_{i,t}$ is raw return of stock i in period t, $r_{f,t}$ is the one-month bill rate. $R_{i,t} - r_{f,t}$ is divided into three parts: the excess return on market portfolio, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB), the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (HML). Data about annual capitalization and book-to-market ratio are obtained from CSMAR database.

We define the residual standard deviation $\varepsilon_{i,t}$ in equation (1) as the idiosyncratic volatility.

$$IVOL_{i,t} = \sqrt{\sum_{t=1}^{T} (\varepsilon_{i,t} - \bar{\varepsilon}_i)^2 / (T-1)} \tag{2}$$

$IVOL_{i,t}$ stands for the idiosyncratic volatility of stock i in period t. Following Bali and Cakici (2008), we use the previous 24 to 60 months of sample returns to compute the standard deviation of residuals in equation (1). To keep consistent, estimated idiosyncratic volatilities are multiplied by twelve to get the annual idiosyncratic volatility.

$$IVOL_{i,t}^{yearly} = 12 \times IVOL_{i,t}^{mont\ hly} \tag{3}$$

Table 1 presents the statistical description of yearly idiosyncratic volatility. It is the mean and standard deviation across Hushen 300 stocks during the period of year 2003 to 2009. As shown in Table 1, the mean of annual idiosyncratic volatility range from 0,986 to 1.979, the standard deviation of annual idiosyncratic volatility range from 0.230 to 1.554.

Table 1

Statistical description of yearly idiosyncratic volatility during sample period

	2004	2005	2006	2007	2008	2009
Mean	1.072	0.986	1.071	1.151	1.412	1.979
Std.Dev.	0.295	0.230	0.245	0.339	0.468	1.554

2.2 Time-series property of idiosyncratic volatility

In AHXZ (2006), they assume the time-series idiosyncratic volatility based on Fama-French three-factor model can be approximated by a random walk process. Using this idiosyncratic volatility measure, they show a strong negative relation between idiosyncratic volatility and expected stock returns. However, Fu (2009) shows that idiosyncratic volatilities estimated from Fama-French three-factor model are time-varying and argue that it is not an appropriate factor to measure the relation between idiosyncratic volatility and the expected stock returns.

Following Fu's method, to confirm whether our idiosyncratic volatilities are time-varying, we run the following time-series regression for each stock,

$$IVOL_{i,t+1} - IVOL_{i,t} = \gamma_{0i} + \gamma_{1i} IVOL_{i,t} + \eta_i$$
$$t = 1,2,\cdots,T, i = 1,2,\cdots,N. \tag{4}$$

For each time series of $IVOL$, we estimate the coefficient γ_1 and then compare its t-statistic with the Dickey-Fuller critical values for the unit-root tests. If the assumption of AHXZ (2006) is correct, i.e. the time-series of $IVOL_t$ follows a random walk process, the coefficient γ_1 should be indistinguishable from zero. On the contrary, if Fu's criticism is correct, i.e. $IVOL_t$ is time-varying, the coefficient γ_1 should be significantly different from 0.

Table 2

Time-series property of idiosyncratic volatility

Table 2 presents the mean, median, the lower, middle and upper quartiles of the γ_1 estimates and the associated t-statistics for regression $IVOL_{i,t+1} - IVOL_{i,t} = \gamma_{0i} + \gamma_{1i} IVOL_{i,t} + \eta_i$, $t = 1,2,\cdots,T, i = 1,2,\cdots,N.$

	Mean	Median	Q1	Q2	Q3
γ_1	-0.013	-0.002	-0.048	-0.003	0.012
t(γ_1)	-0.228	-0.146	-1.413	-0.165	0.877

Table 2 reports the mean, median, the lower, middle and upper quartiles of the γ_1 estimates and the associated t-statistics. The mean γ_1 among Hushen 300 stocks is -0.013 and the average of associated t-statistics is -0.228. Furthermore, at the 5% significance level, we reject the null hypothesis of a random walk in only 24 firms, accounting for 80% of the total number of Hushen 300 firms. At the 10% significance level, we reject the null hypothesis of a random walk in 90% of Hushen 300 firms. The results suggest that the assumption of AHXZ (2006) is correct, i.e. the time-series of $IVOL_t$ follows a random walk process.

2.3 Portfolio analysis

Results in Table 2 suggest that idiosyncratic volatility estimated with the Fama-French three-factor model is a proper measure to analyze the relation between idiosyncratic volatility and expected stock returns. Before running cross-section regression, to compare our result to AHXZ (2006), we first present the results of portfolio analysis.

Every year from 2003 to 2009, quintile portfolios are formed by sorting the Hushen 300 stocks based on their idiosyncratic volatilities estimated using the Fama-French three-factor model. Monthly are calculated based on previous 24 to 60 monthly returns and are changed into annually by multiplying 12 months. Of each idiosyncratic volatility portfolios, annual average returns, annual average market capitalization (size) and annual book-to market ratio are also calculated. The results are reported in Table 3.

As shown in Table 3, there is a strong positive relation between idiosyncratic volatility and expected stocks returns. With the idiosyncratic volatility increase from quintile 1 to 5, the average return difference between quintiles 5 and 1 is 0.44. Table 3 also indicates a strong negative correlation between market capitalization (size) / book-to-market ratio and idiosyncratic volatility, i.e., the smaller (lower) the size (book-to-market ratio) of the company, the higher the stock's idiosyncratic volatility.

Table 3

Portfolios of Hushen 300 stocks sorted by expected idiosyncratic volatility

Every year from 2003 to 2009, quintile portfolios are formed by sorting the Hushen 300 stocks based on their idiosyncratic volatilities estimated using the Fama-French three-factor model. Portfolio 1(5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. Monthly idiosyncratic volatility is calculated based on previous 24 to 60 monthly returns and is changed into annual by multiplying 12 months. Except for idiosyncratic, we also calculate annual expected returns and size, book-to-market-ratio of each idiosyncratic volatility portfolios. Row Q5-Q1 refers to the difference in annual returns between portfolios 5 and 1.

	$LN(ME)$	$LN(BE/ME)$	$IVOL(Annual)$	$Return$
Q1	15.17	-0.90	1.00	0.36
Q2	15.03	-0.94	1.22	0.41
Q3	14.91	-1.04	1.38	0.63
Q4	14.86	-1.02	1.57	0.69
Q5	14.56	-1.27	2.16	0.80
Q5-Q1	0.61	-0.37	1.16	0.44

3. Expected idiosyncratic volatility and expected returns

3.1 Variables

In this section, we run cross-section regressions to explore the cross-sectional relation between expected idiosyncratic volatility and expected average returns. Stocks of Hushen 300 index during the period 2003 to 2009 are included in our dataset. Furthermore, we consider variables that may have effects on the relation between expected idiosyncratic volatility and expected average returns as follows.

1) Beta: According to CAPM, BETA is used to capture the systematic risk, and is estimated based on CAPM.
2) Size: Market capitalization.
3) Book-to-market ratio: Book value divided by market capitalization.

4) Turnover ratio: monthly total trading volume divided by average market capitalization.
5) Reversal$_{-12, 0}$: past 12-month average returns.
6) Institutional (Foreign, State) investor ownership: The number of shares hold by Institutional (Foreign, State) investors divided by the number of shares outstanding.
7) Change in institutional investor ownership: The raw change in the fraction of shares held by institutional investors for stock i over period t divided by the mean change in fractional institutional ownership for all firms over the same period t.

Beta is the measure of systematic risk. We estimate beta based on the cross-section regression approach of Fama and Macbeth (1973) which is also used by Fama and French (1992). In January of each year, all Hushen 300 stocks are sorted by size (market capitalization) then divided into 10 portfolios. For individual stock, we use previous 2 to 5 years of monthly returns to estimate firm betas. Each size decile is subdivided into 10 beta portfolio using the estimated firm beta. We then calculate the monthly returns on the 100 portfolios. For each portfolio, based on CAPM, time-series regressions of portfolio return on the market return are run to get the portfolio beta. The estimated portfolio beta is used as the individual beta.

Following Fama and French (1993), firm size and book-to-market ratio effect expected returns, so we control for the two variables using the natural log in our regression,. Turnover variable are used as a proxy for liquidity. Considering the return momentum effect and herding behavior of institutional investors in China Stock Market, we also control for previous 12-month average return and the change of institutional investors' ownership. Data about investors' ownership come from the annually report of individual firm, others are obtained from the CSMAR database. Table 4 reports the descriptive statistics of above variables during the period 2003 to 2009.

Table 4

Variable descriptive statistics during 2003 to 2009

This table reports the pooled descriptive statistics of stocks that are included in Hushen 300 index during 2003 to 2009. $E[R_t]$ is the expected return of individual stock. Beta is the portfolio beta based on CAPM. Size means the market capitalization. Book-to-market ratio is the book value divided by market capitalization. For size and book-to-market ratio, we take the natural log of each variable. Turnover ratio ($TURN$) is monthly total trading volume divided by average market capitalization. $Reversal_{-12,0}$ is past 12-month average return. Ownership of Institutional (Foreign, State) investor -Own_{Ins}, Own_{For}, Own_{Sta}- is the number of shares hold by Institutional (Foreign, State) investors divided by the number of shares outstanding. The change in institutional investor ownership -ΔOwn_{Ins}- is the raw change in the fraction of shares held by institutional investors for stock i over period t divided by the mean change in fractional institutional ownership for all firms over the same period t.

	Mean	Std.dev.	Median	Kurt	Skew
$E[R_t]$	0.69	1.49	0.14	4.54	1.78
Beta	7.66	5.30	7.68	710.06	24.40
$LN(ME)$	15.12	1.19	15.05	0.31	0.36
$LN(BE/ME)$	-1.07	0.76	-0.97	0.24	-0.66
$TURN$	0.38	0.27	0.31	22.91	2.85
$Reversal_{-12,0}$	0.91	1.40	0.39	5.28	1.92
$IVOL$	0.10	0.03	0.09	13.36	2.42
Own_{Ins}	7.27	7.55	5.38	12.90	2.64
Own_{For}	2.53	7.73	0	15.96	3.95
Own_{Sta}	2.79	7.63	0	32.66	5.25
ΔOwn_{Ins}	1.43	7.17	0.28	25.68	3.49

Table 5

Simple Correlations

This table reports the cross-section correlation of the variable defined in Table 4. Average is taken over 6 years starting in 2003. $E[R_t]$ is the expected return of individual stock. Beta is the portfolio beta based on CAPM. Size is the market capitalization. Book-to-market ratio is the book value divided by market capitalization. For size and book-to-market ratio, we use the nature log of each variables. Turnover ratio ($TURN$) is monthly total trading volume divided by average market capitalization. $Reversal_{-12,0}$ is past 12-month average return. $IVOL_t$ is the idiosyncratic volatility estimated with the Fama-French three-factor model using the previous 24 to 60 monthly returns. Ownership of Institutional (Foreign, State) investor -Own_{Ins}, Own_{For}, Own_{Sta}- is the number of shares hold by Institutional (Foreign, State) investors divided by the number of shares outstanding.

	$E[R_t]$	$Beta$	$LN(ME)$	$LN(BE/ME)$	$TURN$	$Reversal_{-12,0}$	$IVOL_t$	$IVOL_{t-1}$	Own_{Ins}	Own_{For}	Own_{Sta}
$E[R_t]$	1										
$Beta$	0.133	1									
$LN(ME)$	0.304	0.037	1								
$LN(BE/ME)$	0.422	0.125	-0.067	1							
$TURN$	0.376	0.114	0.049	0.180	1						
$Reversal_{-12,0}$	-0.210	0.048	0.039	-0.598	-0.013	1					
$IVOL_t$	0.053	0.060	0.200	-0.133	0.163	-0.098	1				
$IVOL_{t-1}$	0.035	0.100	0.113	-0.162	0.090	-0.075	0.620	1			
Own_{Ins}	0.064	-0.102	0.241	-0.115	-0.134	0.038	0.085	0.072	1		
Own_{For}	-0.006	0.077	0.096	0.014	0.062	-0.031	-0.022	0.006	-0.116	1	
Own_{Sta}	-0.029	-0.002	0.427	-0.024	-0.173	-0.135	0.173	0.170	-0.080	-0.040	1

Table 5 summarizes the cross-section correlations between each pair of these variables. Our primary interest is in the first column－the correlations between expected returns and the other variables. From Table 5 we can find some different results comparing with the portfolio analysis which is reported in Table 3. For example, in Table 5, this is a negative relation between expected returns and idiosyncratic, a positive relation between expected returns and size, book-to-market ratio. However, in Table 3, the smaller the size (book-to-market ratio) of the firm, the higher the stock's idiosyncratic volatility; the higher the expected returns of the firm, the higher the stock's idiosyncratic volatility.

One possible reason of the reversal results of the relation between idiosyncratic volatility and expected returns in Table 3 and 5 is that both market capitalization and book-to-market ratio are very important determinant of expected returns, as we can see in Table 5, the coefficient is 0.35 and 0.39 respectively. Analysis without controlling for size and book-to-market ratio will face a potentially bias. For this reason, we turn to run cross-section regression as follows to capture the relation between expected returns and idiosyncratic volatility,

3.2 Cross-section analysis

3.2.1 Pre-search on expected returns

We start regression analysis by replicating the traditional Fama-French three-factor model. Based on Fama and French (1993), expect for beta, size and book-to-market ratio are two important factors in determining the cross-section returns. Therefore, we first regress annually expected returns on beta, natural log of size and book-to-market ratio which is defined as follow.

$$\mathrm{E}[R_{i,t}] = \rho_{0t} + \sum_{k=1}^{3} \rho_{kt} X_{k,i,t} + \varepsilon_{i,t}, \tag{5}$$

$$X_1 = beta, X_2 = LN(ME), X_3 = LN(BE/ME).$$

Furthermore, previous work has shown that liquidity is typically the dominant determinant of the asset pricing. Amihun and Mendelson (1986) is the earliest of this type of research. They use bid-ask spread to measure the liquidity and argue that stocks with larger spreads have a higher expected returns. To confirm the effect of liquidity on stock returns, we introduce a liquidity variable. Actually, expected for bid-ask spread, trading volumn (Brennan, Chordia and Subrahmanyam, 1998), turnover ratio (Datar, Naik and Radcliffe, 1998; Chui and Wei, 1999) and illiquidity (Amihud, 2002) are also used as a proxy for liquidity. In our paper, we apply turnover ratio as a proxy for liquidity.

Jegadeesh and Titman (1993) show that over an intermediate horizon of 3 to 12 months, past winners on average continue to outperform past losers, i.e. there is momentum in stock prices. However, based on Yang and Qin (2012), in China Stock Markets, past winners on average turn to losers and past losers turn to winners after a horizon of 3 to 12 months, i.e. the stock price reverse. Considering the existing literature discussed above, we add liquidity and reversal factors to equation (1) as follows and name factors in equation (5) as five-factor model.

$$\mathrm{E}\left[R_{i,t}\right] = \rho_{0t} + \sum_{k=1}^{5} \rho_{kt} X_{k,i,t} + \varepsilon_{i,t}, \tag{6}$$

$$X_1 = beta, X_2 = LN(ME), X_3 = LN(BE/ME), X_4 = TURN, X_5 = Reversal_{-12,0}.$$

Panel A of Table 7 summarizes the regression results based on equation (5) and equation (6). We can see the traditional Fama-French three factors have significant power in predicting the cross-section expected returns. Beta is significantly different from 0 under 10% level, and both Ln(ME) and Ln(BE/ME) is significantly different from 0 under 1% level. The coefficient of Ln(ME) is 0.542, which means large firms have higher average returns. This finding is consistent with Fu (2009) but contrasts to the results of existing research in China Stock Market which support the small size effect[2]. When controlling liquidity and reversal factors, beta turns to be not significant even at 10%. Size, book-to-market ratio, turnover ratio is positively related to average expected returns. Previous 12-month returns are negatively related to average expected returns, which suggest that there exists a return reversal in short horizon. T-statistic shows that return reversal is significant at 10% level. By adding liquidity and reversal factors to three-factor model, we have the adjusted R-squared increased from 33.3% to 41.6%.

3.2.2 Cross-section analysis on idiosyncratic volatility and expected returns

We first run a univariate regression of return on idiosyncratic volatility for year t and year t-1. i.e.,

[2] Small firm effect: smaller firms, or firms with a small market capitalization, outperform larger firms. In Fama and French (1993), they also confirm the small firm effect in the U.S. stock markets.

$$\mathrm{E}\left[\mathrm{R}_{i,t}\right] = \rho_{0t} + \varphi_t \mathrm{IVOL}_{i,t} + \varepsilon_{i,t}. \quad (7)$$

$$\mathrm{E}\left[R_{i,t}\right] = \rho_{0t} + \varphi'_t IVOL_{i,t-1} + \varepsilon_{i,t}.$$

Regression results for equation (7) are reported in the first two columns of Panel B in Table 7. The average slopes of $IVOL_t$ is negative and statistically significant at 10% level. Different from the result of portfolio analysis, the results of univariate regression indicate a negative relation between idiosyncratic volatility and expected returns. However, when we regress expected returns on idiosyncratic volatility of year t-1, we cannot find a significant result. Since $IVOL_{t-1}$ seems have no relationship with expected return, so we remove it from the regression analysis.

The difference between portfolio analysis and univariate regression indicate that size and book-to-market ratio have powers in predicting the stock expected returns, analysis without controlling for size and book-to-market ratio will face a potentially bias. For this reason, in order to capture the relation between expected returns and idiosyncratic volatility accurately, we run the following regression.

$$\mathrm{E}\left[\mathrm{R}_{i,t}\right] = \rho_{0t} + \varphi_t \mathrm{IVOL}_{i,t} + \sum_{k=1}^{K} \rho_{kt} \mathrm{X}_{k,i,t} + \varepsilon_{i,t}, \quad (8)$$

$$X_1 = beta, X_2 = LN(ME), X_3 = LN(BE/ME), X_4 = TURN, X_5 = Reversal_{-12,0}$$

$$\mathrm{X}_1 = \mathrm{beta}, \mathrm{X}_2 = \mathrm{LN(ME)}, \mathrm{X}_3 = \mathrm{LN(BE/ME)}.$$

Furthermore, we in addition controls for previous 12-month average returns and turnover ratio.

Panel C and D of Table 7 presents results for equation (8). After controls for beta, size, book-to-market ratio and idiosyncratic volatility, the average slopes of IVOL_t change to positive and statistically significant. Proper explanation of the change in the effect of idiosyncratic volatility on expected returns may be that size, book-to-market ratio, turnover ratio and log returns are very important determinants of expected returns. Therefore, analysis without controlling for size and book-to-market ratio will face a potentially bias. The results do not change when we control in addition for liquidity and reversal factors. The positive relation between idiosyncratic volatility and expected returns is statistically significant at 5% level. Moreover, the adjusted R-squared increases to 34.6% and 42.1% respectively after including $IVOL_t$ in regression (5) and (6).

Table 7

Idiosyncratic volatility and expected returns

$Beta$	$LN(ME)$	$LN(BE/ME)$	$TURN$	$Reversal_{-12,0}$	$IVOL_{t-1}$	$IVOL_t$	R^2
ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	φ	φ'	
Panel A: Results for 3-factor model							
						-0.317	0.006
						(-2.480)*	
Panel B: Results for 5-factor model							
					0.138		0.001
					(1.103)		
Panel C : single regression on idiosyncratic volatility and expected returns							
0.009	0.548	1.016				0.524	0.346
(1.186)	(16.824)***	(18.067)***				(4.516)***	
Panel D : single regression on lag idiosyncratic volatility and expected returns							
0.006	0.502	0.786	1.646	-0.079		0.314	0.421
(0.816)	(14.979)***	(12.014)***	(11.300)***	(-2.222)*		(2.812)**	

Notes: Numbers in parentheses are t-statistics. *, **, *** means the coefficient is different from 0 at 10%, 5%, 1% level respectively.

4. Investors' behavior on the relation between idiosyncratic volatility and expected returns

4.1 Investors' ownership

Investors' ownership is a very important factor on the relation between idiosyncratic volatility and expected returns. Gompers and Metrick (2001) argue that the level of institutional ownership at the end of a quarter has positive predictive power for returns in the nest quarter. Yao and Liu (2007) find that the percentage of institutional ownership is positively related to the return ratio.

To see the effect of investors' ownership on the relation of idiosyncratic volatility and expected returns, we run the regression as follows,

$$\mathrm{E}\left[R_{i,t}\right] = \rho_{0t} + \varphi_t IVOL_{i,t} + \sum_{k=1}^{5} \rho_{kt} X_{k,i,t} + \sum_{m=1}^{2} \pi_{mt} Own_{m,i,t} + \varepsilon_{i,t}, \tag{9}$$

$$X_1 = beta, X_2 = LN(ME), X_3 = LN(BE/ME), X_4 = TURN, X_5 = Reversal_{-12,0},$$

$$M_1 = Institutional, M_2 = States$$

Results for the regression (9) are shown in Panel A of Table 8. After controlling for the factors that have impact on the expected return, we find there is a positive relation between institutional investors' ownership and expected returns. The coefficient of institutional investor ownership is 0.018, and is significant at 5% level. There is a negative relation between the ownership of the States and expected return, and is significant at 1% level. After we control for the ownership of the institutional investors, the foreign investors and the States, we can also find a positive relation between idiosyncratic volatility and expected returns.

4.2 Change of institutional investor ownership

Institutional investors are supposed to follow herd behavior when they invest in the China Stock Market[3]. Following Nofsinger and Sias (1999), herd behavior is defined as a group of investors trading in the same direction over a period of time. As a result, when investors engage in herd behavior, a positive relation between investors' ownership and returns during the same period is supposed to be observed.

To establish the existence of institutional investors' herding, we run the following regression,

[3] Research on herd behavior in China Stock Markets contains:

$$\mathrm{E}[R_{i,t}] = \rho_{0t} + \varphi_t IVOL_{i,t} + \sum_{k=1}^{5} \rho_{kt} X_{k,i,t} + \delta_t \Delta Own_{Ins,i,t} + \varepsilon_{i,t}, \tag{10}$$

$$X_1 = beta, X_2 = LN(ME), X_3 = LN(BE/ME), X_4 = TURN, X_5 = Reversal_{-12,0}.$$

Results in Panel A of Table 8 demonstrate a strong relation between institutional ownership and returns, which means institutional investors herd during investment. The results are statistically significant at the 5% level. Moreover, we find the higher the ownership of the state, the lower the stock return, which indicates that the government plays a vital role in stabilizing the market.

Furthermore, in order to capture the impact of institutional investors' herding on the relation between idiosyncratic volatility and expected returns, we control for the beta, size, book-to-market ratio, turnover ratio, previous 12-month returns, as well as the ownership of institutional investors and states. Panel B of Table 7 presents the results.

Still, we can observe a positive relation between idiosyncratic volatility and expected returns. Besides, there is a positive relation between the ownership of institutional investors and expected returns and a negative relation between the ownership of states and expected returns. After controlling for the ownership of investors, we can still observe a statistically significant positive relation between idiosyncratic volatility and expected returns, but the adjusted R-squared raise to 44.4%.

In summary, the regressions yield strong evidence that idiosyncratic volatility is positively related to average returns. After controlling for beta, size, book-to-market ratio, turnover ratio, previous 12-month average returns, ownership of institutional investors and state, the statistically significant positive relation between idiosyncratic volatility and expected returns still observed.

Comparing with other recent research about China Stock Market, we get the opposite result from Chen et al. (2009) but the same result with Deng and Zhen (2011). In Chen et al. (2009), they calculate the idiosyncratic volatility using the Fama-French three-factor model without concerning for the time-vary property of daily stock returns. Deng and Zhen (2011) confirms there exist a time-vary property between daily stock returns and find a positive relation between idiosyncratic volatility based on ARMA model and expected returns. Using monthly stock returns, we also find a positive relation between idiosyncratic volatility based on Fama-French three-factor model and expected annual returns. Besides, being different from the existing literature on China Stock Market, we also consider the impact of institutional investors' herding on the relation between idiosyncratic volatility and expected returns and find even control for the herding factors, the statistically significant positive relation is still holding.

Table 8

Investors' behavior on the relation between idiosyncratic volatility and expected returns

$Beta$	$LN(ME)$	$LN(BE/ME)$	$TURN$	$Reversal_{-12,0}$	$IVOL_t$	Own_{Ins}	Own_{For}	Own_{Sta}	ΔOwn_{Ins}	R^2
ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	φ	π_1	π_2	π_3	δ	
Panel A: Investors' ownership										
0.007	0.513	0.772	1.610	-0.081	0.327	0.018		-0.024		0.444
(1.060)	(14.420)***	(11.962)***	(11.005)***	(-2.298)*	(2.988)**	(3.594)***		(-4.820)***		
Panel B: herding of institutional investors										
0.007	0.500	0.786	1.707	-0.093	0.308				0.010	0.428
(1.019)	(15.004)***	(12.079)***	(11.702)***	(-2.595)**	(2.772)**				(3.495)***	

Notes: Numbers in parentheses are t-statistics. *, **, *** means the coefficient is different from 0 at 10%, 5%, 1% level respectively.

5. Conclusion

"High risk, high return." is commonly received during a financial investment. However, AHXZ's finding suggests high idiosyncratic volatility brings low expected returns. Chen et al. (2009) find the idiosyncratic volatility puzzle also exists in China Stock Market. Using monthly stock returns, we find there is a significantly positive relation between idiosyncratic volatility and expected returns. However, after controlling for size, book-to-market ratio, liquidity, momentum, herding of institutional investors, positive relation between idiosyncratic volatility and expected returns turn to be negative. This result indicates that in Chinese Stock Market, the idiosyncratic volatility puzzle is just an apparent phenomenon.

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