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Does idiosyncratic volatility matter? — Evidence from Chinese stock market☆

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HIGHLIGHTS

- A new method is applied to estimate idiosyncratic volatility.
- The idiosyncratic volatility is positively related to expected return.
- Positive relation disappears when using alternate estimate method.
- In China, the idiosyncratic volatility premium is just an apparent phenomenon.

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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 positive relation between idiosyncratic volatility and expected returns when we use Fama–French five-factor model to estimate idiosyncratic volatility. However, the positive relation disappears when we use GARCH (1,1) model to estimate idiosyncratic volatility. This result indicates that in Chinese Stock Market, the idiosyncratic volatility premium is just an apparent phenomenon, whether the idiosyncratic volatility matter or not depend on the way we estimate the idiosyncratic volatility. The result is robust after controlling for investors' lottery preference, investors' sentiment and other factors.

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 [1] theoretically proves that when investors with few stocks in his portfolios, idiosyncratic volatility plays an important role in determining equilibrium asset price. Merton [2] points out investors with incomplete information demand a return compensation for bearing idiosyncratic risk.

Supporting the theoretical results, Malkiel and Xu [3] confirm that portfolios with higher idiosyncratic volatility have higher average returns, because investors who cannot hold a fully diversified portfolio demand a return compensation.

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Spiegel and Wang [4], Chua et al. [5] and Fu [6] 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 et al. [7, 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 existing literature and is called "idiosyncratic volatility puzzle". For further confirming, Ang et al. [8] 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 [9] further clarify the existence and significance of the "idiosyncratic volatility puzzle" found in [7]. They indicate that cross-section relation between idiosyncratic risk and expected returns depends on the calculation of idiosyncratic volatility and average portfolio returns, and exclusion of smallest, lowest priced, and least liquid stocks from the sample.

Fu [6] 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 EGARCH model to estimate expected idiosyncratic volatility, and finds they are positively related to expected returns. Following Fu's method, based on international data, Brockman et al. [10] use the EGARCH method to estimate conditional idiosyncratic volatility and confirm Fu's results.

Several empirical results attribute the idiosyncratic volatility puzzle to investors' preference of lottery-like assets. Bali et al. [11] use maximum daily return as an indicator for stocks that are preferred by lottery-seeking investor, find including maximum daily return reverses the puzzling negative relation between idiosyncratic volatility and return. Hou and Loh [12] further evaluate the potential explanations of lottery preference on idiosyncratic volatility puzzle. They find lottery preference show some promise in explaining the puzzle.

Huang et al. [13] 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 et al. [14] 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.

Chen and Petkova [15] 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 et al. [16, in Chinese] 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 et al. [17] 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 [18, in Chinese] apply ARMA model to calculate the expected idiosyncratic volatility. Basing on Chinese Stock Market data from 1997 to 2009, they find idiosyncratic volatility puzzle disappears.

The purpose of this paper is to clarify the relation between idiosyncratic volatility and expected returns in China Stock Market. We also detect the reason why existing literature about China Stock Market presenting conflicting evidence. As mentioned by AHXZ, the relation between idiosyncratic volatility and expected return may depend on how it be estimated. Therefore, we apply two ways to estimate idiosyncratic volatility, residual of FF five-factor model and GARCH (1,1) model. Using all A stocks listed on Shanghai and Shenzhen Stock Exchange, we show the time-series of idiosyncratic volatility calculated using the GARCH (1,1) model is independent, i.e., it is a more suitable proper proxy to describe the stocks' idiosyncratic volatility process as a random walk.

Regression analysis indicates there is a positive relation between idiosyncratic volatility based on five-factor model and expected returns. To further confirm the positive relation observed, we control for some variables: size, book-to-market ratio, turnover, lag annual return, ownership of institutional investors, lottery preference, actual controller property and investors' sentiment. We find after controlling these variables, positive relation is still robust, which imply the idiosyncratic volatility premium in China exist when we use five-factor model to estimate idiosyncratic volatility. However, when we use GARCH model to estimate idiosyncratic volatility, the positive relation disappears. The result implies that the idiosyncratic volatility do not matter!

The rest of the paper is organized as follows. Section 2 describes the method we apply to calculate idiosyncratic volatility and its time-series properties. Section 3 examines the relation between idiosyncratic volatility and expected returns in portfolio version. Section 4 examines the relation between idiosyncratic volatility and expected returns in cross-section version. Section 5 concludes the paper.

2. Idiosyncratic volatility and time-series property

2.1. Estimation of idiosyncratic volatility

The data include all A stocks from Shanghai and Shenzhen Stock Exchange for the period from 1997 to 2016. Following AHXZ, we first apply Fama–French three-factor model to estimate idiosyncratic volatility of individual stocks.

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

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - r_{f,t}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{1}$$

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 five 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[1] database. We use daily stock returns to generate the idiosyncratic volatility. Daily returns are obtained from the CSMAR database.

We define the residual standard deviation $\varepsilon_{i,t}$ in Eq. (1), i.e., in FF three-factor model, as the idiosyncratic volatility.

$$IVOL(FF3)_{i,t} = \sqrt{\sum_{t=1}^{T} (\varepsilon_{i,t} - \overline{\varepsilon}_i)^2 / (T-1)} \tag{2}$$

$IVOL_{i,t}$ stands for the idiosyncratic volatility of stock i in period t. We use the daily returns of previous one year to compute the standard deviation of residuals in Eq. (1). To keep consistent, estimated idiosyncratic volatilities are multiplied by actual trading days to get the annual idiosyncratic volatility.

$$IVOL_{i,t}^{yearly} = N \times IVOL_{i,t}^{daily} \tag{3}$$

where N is the actual trading days in year t. Given the evidence that Fama and French [19] find a five-factor including size, value, profitability and investment performs better than three-factor model, we run FF five-factor model as follows.

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - r_{f,t}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t} \tag{4}$$

where *RMW* is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, *CMA* is the difference between the returns on diversified portfolios of the stocks of low and high investment firms. Also, we measure the idiosyncratic volatility with the daily residual standard deviation, and convert into annual idiosyncratic volatility, called $IVOL(FF5)_{i,t}$.

In order to well describe the time-series idiosyncratic volatility, we apply GARCH (1,1) model to calculate idiosyncratic volatility. The function forms are as follows.

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - r_{f,t}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} \sim N\left(0, \sigma_{i,t}^2\right), \tag{5}$$

$$\sigma_{i,t}^2 = a_{i,t} + b_{i,t}\varepsilon_{i,t-1}^2 + c_{i,t}\sigma_{i,t-1}^2 \tag{6}$$

We define the unconditional variance in Eq. (6) as the idiosyncratic volatility.

$$IVOL\,(GARCH)_{i,t} = \frac{a_{i,t}}{1 - \left(b_{i,t} + c_{i,t}\right)} \tag{7}$$

We use the daily returns of previous one year to compute $IVOL\,(GARCH)_{i,t}$. To keep consistent, estimated idiosyncratic volatilities are multiplied by actual trading days to get the annual idiosyncratic volatility.

Table 1 presents the statistical description of annual idiosyncratic volatility. It is the mean and standard deviation across all A stocks listed in Shanghai and Shenzhen Stock Exchange during the period of year 1997 to 2016. As shown in Table 1, the mean of annual idiosyncratic volatility based on FF three-factor model and FF five-factor model nearly have no difference, both are smaller than that based on GARCH model.

2.2. Time-series property of idiosyncratic volatility

AHXZ, 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 [6] 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.

1 CSMAR® China Stock Market Trading Database.

Table 1
Statistical description of annual idiosyncratic volatility during sample period.

	$IVOL(FF5)$	$IVOL(GARCH)$
Mean	0.110	0.159
Std. Dev.	0.069	2.714
Median	0.094	0.097

Table 2
Time-series property of idiosyncratic volatility. Table 2 presents γ_1 estimates and the associated t-statistics for regression $IVOL_{i,t+1} - IVOL_{i,t} = \gamma_{0i} + \gamma_{1i} IVOL_{i,t} + \eta_i$, $t = 1, 2, \ldots, T, i = 1, 2, \ldots, N$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$IVOL(FF5)$	$IVOL(GARCH)$
γ_1	-0.493^{***}	-1.471
$t(\gamma_1)$	-63.949	-0.168

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

$$IVOL_{i,t+1} - IVOL_{i,t} = \gamma_{0i} + \gamma_{1i} IVOL_{i,t} + \eta_i$$
$$t = 1, 2, \ldots, T, i = 1, 2, \ldots, N. \tag{8}$$

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 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 reports the γ_1 estimates and the associated t-statistics. In FF five-factor method, the coefficient γ_1 is -0.493, associated t-statistics is significant at the 1% significance level. As a result, we reject the null hypothesis of a random walk. On the other hand, in GARCH method, the coefficient γ_1 is -1.471, with a t-statistics of -0.168, which are not significant at the even 10% significance level. Therefore, the IVOL calculated by GARCH follow a random walk. The results suggest that the idiosyncratic volatility estimated with the GARCH (1,1) model is a nearest measure to AHXZ and is a proper measure to analyze the relation between idiosyncratic volatility and expected stock returns.

3. Portfolio analysis

Results in Table 2 suggest that idiosyncratic volatility estimated with the GARCH (1,1) 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, we first present the results of portfolio analysis.

Every year from 1997 to 2016, quintile portfolios are formed by sorting all sample stocks based on their idiosyncratic volatilities estimated using the Fama–French five-factor model and GARCH (1,1) model respectively. Of each idiosyncratic volatility portfolios, annual equal-weighted and value-weighted returns, as well as Jensen's alpha with respect to FF three-factor and five-factor model are calculated. The results are reported in Table 3.

Panel A of Table 3 shows the results based on FF five-factor model. In panel A, the value-weighted return increase from 0.311% per year for quintile 1 to 0.797% per year for quintile 5. Therefore, the value-weighted raise as the idiosyncratic volatility raise. However, in case of the equal-weighted return, it increase from 0.339% per year going from quintile 1 to 0.356% per year for quintile 4. Then, in quintile 5, it drop to 0.335%. The difference in equal-weighted return between quintile portfolio 5 and 1 is -0.004%. As the idiosyncratic volatility raise, the expected returns do not show a clear trend.

Panel B of Table 3 shows the results based on GARCH model. In panel B, the value-weighted return increase from 0.322% per year going from quintile 1 to 0.756% per year for quintile 4. Then, in quintile 5, it has a slight drop to 0.663%. The difference in value-weighted return between quintile portfolio 5 and 1 is 0.341%. In case of equal-weighted return, still cannot observe obvious relation trend when idiosyncratic volatility raise. The difference between quintile portfolio 5 and 1 is -0.012%.

4. Idiosyncratic volatility and expected returns

4.1. Variables

In this section, we run cross-section regressions to explore the cross-sectional relation between idiosyncratic volatility and expected average returns. Stocks of all A stock from Shanghai and Shenzhen Stock Exchange during the period 1997 to 2016 are included in our dataset. Furthermore, we consider candidate variables that may have effects on the relation between idiosyncratic volatility and expected average returns as follows.

Table 3
Portfolios of sample stocks sorted by idiosyncratic volatility. Every year from 1997 to 2016, quintile portfolios are formed by sorting all sample stocks based on their idiosyncratic volatilities estimated using the Fama–French five-factor model and GARCH (1,1) model. Q1(5) is the portfolio of stocks with the lowest (highest) idiosyncratic volatilities. We also calculate equal weight and value weight annual returns as well as Jensen's alpha with respect to the FF three-factor and five-factor model of each portfolios. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Mean				alpha-3	alpha-5
	IVOL	*EWRet*	*VWRet*		
Panel A: IVOL based on FF five-factor model					
Q1	0.056	0.339	0.311	0.939***	1.161***
				(9.390)	(12.600)
Q2	0.083	0.359	0.506	0.965***	1.186***
				(10.457)	(11.504)
Q3	0.104	0.354	0.515	0.882***	1.098***
				(8.796)	(11.507)
Q4	0.132	0.356	0.658	0.971***	1.184***
				(9.814)	(12.302)
Q5	1.592	0.335	0.797	0.938***	1.128***
				(10.104)	(12.730)
Panel B: IVOL based on GARCH model					
Q1	0.050	0.331	0.322	0.959***	1.132***
				(9.717)	(11.655)
Q2	0.083	0.349	0.517	0.954***	1.163***
				(9.175)	(11.583)
Q3	0.107	0.349	0.518	0.957***	1.150***
				(9.357)	(11.725)
Q4	0.137	0.347	0.756	1.022***	1.204***
				(11.137)	(13.520)
Q5	0.364	0.319	0.663	0.929***	1.128***
				(9.775)	(12.448)

We divide control variables into three categories: the basic feather group, the market frictions group, investors' related group. **The basic feather group** include market beta (*Beta*), stock size (*ME*) and book-to-market ratio (*BE/ME*), we control for *ME* and *BE/ME* variables using the natural log in our regression. We obtain related data from CSMAR database.

***BETA*:** According to CAPM, beta is used to capture the systematic risk, and is estimated based on CAPM.

***ME*:** Based on Fama–French three-factor model, market capitalization is another variable to capture the systematic risk. We use the natural logarithmic form of the market value.

***BE/ME*:** Based on Fama–French three-factor model, book-to-market ratio is also a variable to capture the systematic risk. We use the natural logarithmic form of book value divided by market value.

The market frictions group contains return reversal effect (*Lagret*) and liquidity premium (*Turn*). We obtain related data from CSMAR database.

***Lagret*:** The idiosyncratic volatility puzzle may driven by stock return reversals, which are proposed by Huang et al. [13]. We measure lag annual return as the candidate variables of return reversal.

***Turn*:** Bali and Cakici [9] find after exclude the least liquid stocks, idiosyncratic volatility puzzle disappear, which indicate liquidity plays a crucial role in determining the relation between idiosyncratic volatility and expected return. Therefore, we add turnover ratio as the candidate variables of liquidity, which equals to total trading volume divided by average market value.

Investors' related group contains institutional investors' ownership (*Insown*), property of the actual controller (*PAC*), lottery preference of investors (*Lotpre*) and investors' sentiment index (*ISI*). Data about institutional investors' ownership and property of the actual controller come from WIND database, others are obtained from the CSMAR database.

***Insown*:** According to Fu [6], institutional investors can hold more diversified portfolios than individual investors, and therefore do not care much about a stock in the portfolio. When stocks are less held by institutional investors, the positive correlation between idiosyncratic volatility and stocks return is stronger. In this paper, we use Institutional investors' ownership as a candidate variables.

Table 4
Variable descriptive statistics during 1997 to 2016. This table reports the pooled descriptive statistics of control variable on stocks that are included in all A stocks from Shanghai and Shenzhen Stock Exchange during 1997 to 2016. *Return* is annual return in year t. *Beta* is the portfolio beta based on CAPM in year t−1. *ME* means the market capitalization in year t−1. *BE/ME* is the book value divided by market capitalization in year t−1. For *ME* and *BE/ME*, we take the natural log of each variable. *Turn* is total trading volume divided by average market capitalization in year t−1. *Lagret* is annual return in year t−1. *Insown* is the number of shares hold by Institutional investors divided by the number of shares outstanding in year t−1. *PAC* is a dummy, it equals to 1 if the company is state-owned and 0 otherwise. *Lotpre* is maximum daily return in year t−1. *ISI* is a regression on new account, lag market turnover, lag consumer's confidence index, lag average discount rate of closed-end fund, lag numbers of IPO and lag average return on the first day of IPO in year t−1.

	Mean	Std.dev.	Median	Skew	Kurt
Return	0.305	0.824	0.074	2.397	11.022
Beta	1.080	0.231	1.093	−0.271	0.709
LN(*ME*)	14.356	1.223	14.268	0.546	0.611
LN(*BE*/*ME*)	6.510	0.865	6.523	−0.378	1.829
Turn	4.552	3.368	3.616	1.645	3.624
Lagret	0.263	0.820	0.026	2.534	11.687
Insown	24.115	25.604	14.658	0.784	−0.571
PAC	0.609	0.488	1.000	−0.449	−1.799
Lotpre	0.093	0.023	0.100	6.336	132.371
ISI	46.554	26.476	43.324	2.351	5.080

PAC**:** Foreign scholars proposed different explanations for idiosyncratic volatility puzzle based on different perspectives, but they mainly focus on American Stock Market. China's stock market has experienced a unique development process and evolution path, therefore, the "state-owned stock" may also be one of the causes of the idiosyncratic volatility puzzle in Chinese Stock Market. We use property of actual controller as the proxy variable of the "state-owned stock", it equals to 1 if the company is state-owned and 0 otherwise.

Lotpre**:** Based on the conclusion of Bali et al. [11] and Hou and Loh [12], lottery preference also have explanatory power for the idiosyncratic volatility puzzle. Here, we use maximum daily return as a candidate variables of lottery preference of investors.

ISI**:** Investors' sentiment may also affect stock returns. It is a regression on new account, lag market turnover, lag consumer's confidence index, lag average discount rate of closed-end fund, lag numbers of IPO and lag average return on the first day of IPO.

Table 4 reports the descriptive statistics of above variables during the period 1997 to 2016. The average annual return is 0.31% with a standard deviation of 0.82%. The average *Beta*, *LN(ME)*, *LN(BE/ME)*, *Turn*, *Lagret*, *Insown*, *Lotpre*, *ISI* are 1.08, 14.36, 6.51, 4.55, 0.26, 24.11, 0.09, 46.55, respectively.

Table 5 summarizes the cross-section correlations between each pair of these variables. In Panel A of Table 5, we calculate *IVOL* using the residual of FF five-factor model. Our primary interest is in the first column — the correlations between expected returns and the other variables, especially with *IVOL*. There is a positive relation between expected returns and idiosyncratic volatility, the correlation is 0.06, i.e., the higher the stock's idiosyncratic volatility, the higher the expected returns of the firm. And there also exist a positive relation between expected returns and book-to-market ratio, lottery preference. However, the relation between expected return and beta, size, turnover, lag return, institutional ownership, property of actual controller, investors' sentiment is negative.

In Panel B of Table 5, we calculate *IVOL* using GARCH (1,1) model. The correlations between expected returns and *IVOL* is −0.005, which is in contract to the result in Panel A, it means the higher the stock's idiosyncratic volatility, the lower the expected returns of the firm. The relation between expected return and other variables stay constant.

4.2. Cross-section analysis

4.2.1. 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.,

$$\mathrm{E}\left[\mathrm{R}_{\mathrm{i,t}}\right] = \rho_{0\mathrm{t}} + \varphi_{\mathrm{t}}\mathrm{IVOL}_{\mathrm{i,t-1}} + \varepsilon_{\mathrm{i,t}}. \tag{9}$$

Regression results for Eq. (9) using FF five-factor model to estimate IVOL are reported in the first two raw (Model 1) of Table 6. The average slopes of IVOL is positive 1.192 and statistically significant at 1% level. Different from the result of portfolio analysis, the results of univariate regression indicate a positive relation between idiosyncratic volatility and expected returns.

Table 5
Simple correlations. This table reports the pooled descriptive statistics of control variable on stocks that are included in all A stocks from Shanghai and Shenzhen Stock Exchange during 1997 to 2016. *Return* is annual return in year t. *Beta* is the portfolio beta based on CAPM. *ME* means the market capitalization in year t. *BE/ME* is the book value divided by market capitalization in year t. For *ME* and *BE/ME*, we take the natural log of each variable. *Turn* is total trading volume divided by average market capitalization in year t. *Lagret* is past annual return in year t. *Insown* is the number of shares hold by Institutional investors divided by the number of shares outstanding in year t. *PAC* is a dummy, it equals to 1 if the company is state-owned and 0 otherwise. *Lotpre* is maximum daily return in year t. *ISI* is a regression on new account, lag market turnover, lag consumer's confidence index, lag average discount rate of closed-end fund, lag numbers of IPO and lag average return on the first day of IPO. In Panel A, we calculate *IVOL* using the residual of FF five-factor model. In Panel B, we calculate *IVOL* using GARCH (1,1) model.

	Return	*Beta*	*LN(ME)*	*LN(BE/ME)*	*Turn*	*Lagret*	*Insown*	*Lotpre*	*PAC*	*ISI*	*IVOL(FF5)*
Panel A											
R_t	1										
Beta	−0.037	1									
LN(ME)	−0.218	−0.008	1								
LN(BE/ME)	0.198	0.088	−0.4055	1							
Turn	−0.058	0.151	−0.0697	−0.210	1						
Lagret	−0.153	−0.110	0.2475	−0.346	0.452	1					
Insown	−0.095	−0.044	0.6748	−0.369	−0.282	0.056	1				
Lotpre	0.158	0.207	−0.0194	−0.043	0.279	0.228	−0.047	1			
PAC	−0.027	0.008	0.0402	0.159	−0.093	−0.013	0.047	0.007	1		
ISI	−0.324	−0.076	0.2487	−0.331	0.491	0.540	0.069	0.139	0.003	1	
IVOL(FF5)	0.062	0.026	−0.0197	−0.284	0.603	0.492	−0.079	0.462	−0.027	0.550	1
	Return	*Beta*	*LN(ME)*	*LN(BE/ME)*	*Turn*	*Lagret*	*Insown*	*Lotpre*	*PAC*	*ISI*	*IVOL(GARCH)*
Panel B											
R_t	1										
Beta	−0.037	1									
LN(ME)	−0.217	−0.008	1								
LN(BE/ME)	0.198	0.088	−0.406	1							
Turn	−0.058	0.151	−0.070	−0.210	1						
Lagret	−0.153	−0.110	0.247	−0.346	0.451	1					
Insown	−0.095	−0.044	0.675	−0.369	−0.282	0.056	1				
Lotpre	0.158	0.206	−0.019	−0.043	0.279	0.228	−0.047	1			
PAC	−0.027	0.008	0.040	0.159	−0.093	−0.013	0.047	0.007	1		
ISI	−0.324	−0.076	0.249	−0.331	0.491	0.540	0.069	0.139	0.003	1	
IVOL(GARCH)	−0.005	−0.006	−0.004	−0.001	0.033	0.019	−0.018	0.032	0.011	0.025	1

The difference between portfolio analysis and univariate regression indicate that other control variables have powers in predicting the stock expected returns, analysis without controlling for them 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.

$$E\left[R_{i,t}\right] = \rho_{0t} + \varphi_t IVOL_{i,t-1} + \sum_{k=1}^{K} \rho_{kt} X_{k,i,t} + \varepsilon_{i,t}, \tag{10}$$

$$X_1 = Beta, X_2 = LN\,(ME)\,, X_3 = LN(BE/ME), X_4 = Turn, X_5 = Lagret$$
$$X_6 = Insown, X_7 = Lotpre, X_8 = PAC, X_9 = ISI.$$

Model 2 of Table 6 presents results for the effect of beta, size, book-to-market ratio on the relation of expected return and idiosyncratic volatility. The average slopes of $IVOL_t$ is positive 1.890 and statistically significant at 1% level. Proper explanation of the change in the effect of idiosyncratic volatility on expected returns may be that size, book-to-market ratio, turnover ratio are very important determinants of expected returns. Therefore, analysis without controlling for size and book-to-market ratio will face a potentially bias.

Model 3 and 4 of Table 6 indicate that the results do not change when we control in addition for liquidity and momentum factors. The positive relation between idiosyncratic volatility and expected returns is statistically significant at 1% level.

Investors' ownership is a very important factor on the relation between idiosyncratic volatility and expected returns. Gompers and Metrick [20] argue that the level of institutional ownership at the end of a quarter has positive predictive power for returns in the next quarter. Yao and Liu [21] find that the percentage of institutional ownership is positively related to stock return.

Results about institutional ownership effect are shown in Model 5 of Table 6. 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 0.007, and is statistically significant at 1% level. After we control for the ownership of the institutional investors, we can also find a positive relation between idiosyncratic volatility and expected returns.

Model 6–8 in Table 6 also yield striking evidence that expected return is positively related to idiosyncratic volatility in the cross-section after controlling for investors' behavior. Model 6 consider investors' lottery preference when investing,

Table 6
Cross-section analysis on idiosyncratic volatility and expected returns: IVOL based on FF five-factor model. We run a firm-level cross-sectional regressions of stock return on lag idiosyncratic volatility and lag controlling variables each year from 1997 to 2016. Explained variable is annual return on year t. *Beta* is the portfolio beta based on CAPM on year t−1. *ME* is the market capitalization in year t−1. *BE/ME* is the book value divided by market capitalization in year t−1. For *ME* and *BE/ME*, we take the natural log of each variable. *Turn* is total trading volume divided by average market capitalization in year t−1. *Lagret* is past annual return in year t−1. *Insown* is the number of shares hold by Institutional investors divided by the number of shares outstanding in year t−1. *PAC* is a dummy, it equals to 1 if the company is state-owned and 0 otherwise. *Lotpre* is maximum daily return in year t−1. *ISI* is a regression on new account, lag market turnover, lag consumer's confidence index, lag average discount rate of closed-end fund, lag numbers of IPO and lag average return on the first day of IPO on year t−1. *IVOL* is the idiosyncratic volatility in year t. We calculate IVOL using the residual of FF five-factor model. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Model	*Beta*	*LN(ME)*	*LN(BE/ME)*	*Turn*	*Lagret*	*Insown*	*Lotpre*	*PAC*	*ISI*	*IVOL*	R^2
1										1.192***	0.010
										(11.755)	
2	−0.171***	−0.060***	0.186***							1.890***	0.066
	(−6.282)	(−10.787)	(22.669)							(19.847)	
3	−0.114***	−0.064***	0.179***	−0.027***						2.699***	0.073
	(−4.121)	(−11.625)	(21.810)	(−11.195)						(22.633)	
4	−0.205***	−0.040***	0.163***	−0.016***	−0.169***					3.307***	0.090
	(−7.354)	(−6.998)	(19.897)	(−6.225)	(−17.498)					(26.852)	
5	−0.226***	−0.125***	0.183***	−0.006**	−0.152***	0.006***				2.980***	0.108
	(−8.166)	(−16.889)	(22.317)	(−2.304)	(−15.812)	(17.692)				(24.159)	
6	−0.315***	−0.127***	0.176***	−0.003	−0.161***	0.007***	4.298***			1.713***	0.118
	(−11.177)	(−17.261)	(21.571)	(−1.017)	(−16.821)	(18.952)	(14.101)			(17.466)	
7	−0.350***	−0.119***	0.159***	−0.019***	−0.152***	0.003***	6.010***	−0.099***		1.897***	0.129
	(−10.437)	(−14.108)	(15.631)	(−6.448)	(−14.265)	(6.838)	(17.627)	(−6.427)		(12.718)	
8	−0.460***	−0.055***	0.145***	0.006**	−0.054***	0.003***	4.052***	−0.070***	−0.015***	2.849***	0.231
	(−14.530)	(−6.763)	(15.238)	(2.145)	(−5.219)	(6.781)	(12.506)	(−4.860)	(−40.992)	(25.991)	

after control for daily max return, the average slope is 1.713, and is significant at 1% level. The slope of variable *Lotpre* is 4.298, which means investor invest in lottery-like stock require a positive premium. Model 7 study on the actual controller's property. It has a negative effect on expected annual return, which means the higher the state own of a company, the lower of its return. After controlling for actual controller's property of a company, the relation between expected return and idiosyncratic volatility is still positive. The average slope of *IVOL* is 1.897, with the t-statistic 12.718. Model 8 further consider the effect of investors' sentiment on expected return. Obviously, the affect is negative, the average slope of *ISI* is −0.015. After controlling for investors' sentiment, the relation between expected return and idiosyncratic volatility is still positive. The average slope of *IVOL* is 2.849, with the t-statistic 25.991, statistically significant at 1% level.

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, momentum, ownership of institutional investors, investor's lottery preference, actual controller's property of a company, as well as investors' sentiment, 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. [16, in Chinese] but the same result with Deng and Zheng [18]. In Chen et al. [16, in Chinese], 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 Zheng [18] 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 7 list the cross-sectional result using GARCH (1,1) model to calculate *IVOL*. Compare to Table 6, we get a opposite result. The relation between expected return and idiosyncratic volatility is negative. However, the negative relation is statistically insignificant. We keep the result to the fourth place after the decimal point. The result stay constantly no matter we control for beta, size, book-to-market ratio, turnover, momentum, ownership of institutional investors, investor's lottery preference, actual controller's property of a company nor investors' sentiment.

We use two way to calculate the idiosyncratic volatility and get two diametrically opposed result. When using the residual of FF five-factor to estimate idiosyncratic volatility, the relation between expected return and idiosyncratic volatility is positive, and the positive relation is robust after controlling for company size, book-to-market value, investors' property, and investors' behavior. However, when using GARCH (1,1) model to estimate idiosyncratic volatility, the relation between expected return and idiosyncratic volatility is negative, but the t-statistic is insignificant. Therefore, whether idiosyncratic volatility is priced depends on the way it be estimated.

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. [16, in Chinese] find the idiosyncratic volatility puzzle also

Table 7
Cross-section analysis on idiosyncratic volatility and expected returns: IVOL based on GARCH model. We run a firm-level cross-sectional regressions of stock return on lag idiosyncratic volatility and lag controlling variables each year from 1997 to 2016. Explained variable is annual return on year t. *Beta* is the portfolio beta based on CAPM on year t−1. *ME* is the market capitalization in year t−1. *BE/ME* is the book value divided by market capitalization in year t−1. For *ME* and *BE/ME*, we take the natural log of each variable. *Turn* is total trading volume divided by average market capitalization in year t−1. *Lagret* is past annual return in year t−1. *Insown* is the number of shares hold by Institutional investors divided by the number of shares outstanding in year t−1. *PAC* is a dummy, it equals to 1 if the company is state-owned and 0 otherwise. *Lotpre* is maximum daily return in year t−1. *ISI* is a regression on new account, lag market turnover, lag consumer's confidence index, lag average discount rate of closed-end fund, lag numbers of IPO and lag average return on the first day of IPO on year t−1. *IVOL* is the idiosyncratic volatility in year t. We calculate *IVOL* using GARCH (1,1) model. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Model	*Beta*	*LN(ME)*	*LN(BE/ME)*	*Turn*	*Lagret*	*Insown*	*Lotpre*	*PAC*	*ISI*	*IVOL*	R^2
1										−0.0007	0.000
										(−0.275)	
2	−0.147***	−0.070***	0.137***							−0.0006	0.043
	(−5.333)	(−12.620)	(17.272)							(−0.274)	
3	−0.162***	−0.068***	0.143***	0.006***						−0.0009	0.044
	(−5.780)	(−12.170)	(17.509)	(3.125)						(−0.404)	
4	−0.220***	−0.055***	0.130***	0.017***	−0.096***					−0.0008	0.050
	(−7.729)	(−9.530)	(15.662)	(7.612)	(−10.121)					(−0.343)	
5	−0.243***	−0.156***	0.157***	0.025***	−0.084***	0.007***				−0.0005	0.075
	(−8.649)	(−21.006)	(19.039)	(11.110)	(−8.987)	(21.167)				(−0.220)	
6	−0.367***	−0.149***	0.155***	0.020***	−0.118***	0.008***	6.189***			−0.0017	0.101
	(−12.949)	(−20.380)	(19.050)	(9.107)	(−12.601)	(22.100)	(21.412)			(−0.750)	
7	−0.387***	−0.136***	0.137***	−0.003	−0.119***	0.003***	7.674***	−0.088***		−0.0024	0.118
	(−11.509)	(−16.197)	(13.650)	(−1.001)	(−11.473)	(7.969)	(24.196)	(−5.710)		(−1.000)	
8	−0.504***	−0.098***	0.110***	0.030***	−0.014	0.004***	7.469***	−0.057***	−0.012***	−0.0017	0.190
	(−15.545)	(−12.126)	(11.320)	(11.143)	(−1.386)	(8.920)	(24.565)	(−3.849)	(−33.578)	(−0.737)	

exists in China Stock Market. Using all A stocks in Shanghai and Shenzhen Stock Exchange during 1997 to 2016, we find there is a significantly positive relation between idiosyncratic volatility based on FF five-factor model and expected returns. The result is robust after controlling for size, book-to-market ratio, liquidity, momentum, ownership of institutional investors, lottery preference, actual controller's property of firms, as well as investors' sentiment. However, using GARCH model to estimate idiosyncratic volatility, the relation between idiosyncratic volatility and expected returns turn to be negative. This result indicates that in Chinese Stock Market, the idiosyncratic volatility matter or not depend on the way the idiosyncratic volatility be estimated.

References

[1] H. Levy, Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio, Amer. Econ. Rev. 68 (1978) 643–658.
[2] R.C. Merton, A simple model of capital market equilibrium with incomplete information, J. Finance 42 (1987) 483–510.
[3] B.G. Malkiel, Y. Xu, Idiosyncratic risk and security returns. Working paper, University of Texas at Dallas, 2002.
[4] M. Spiegel, X. Wang, Cross-sectional variation in stock returns: liquidity and idiosyncratic risk. Working paper, Yale University, 2006.
[5] C.T. Chua, J. Goh, Z. Zhang, Expected volatility, unexpected volatility, and the cross-section of stock returns, J. Financ. Res. 33 (2) (2010) 103–123.
[6] F. Fu, Idiosyncratic risk and the cross-section of expected stock returns, J. Financ. Econ. 91 (2009) 24–37.
[7] A. Ang, R.J. Hodrick, Y. Xing, X. Zhang, The cross-section of volatility and expected returns, J. Finance 61 (2006) 259–299.
[8] A. Ang, R.J. Hodrick, Y. Xing, X. Zhang, High idiosyncratic volatility and low returns: International and further U. S. evidence, J. Financ. Econ. 91 (2009) 1–23.
[9] T. Bali, N. Cakici, Idiosyncratic volatility and the cross-section of expected returns, J. Financ. Quant. Anal. 43 (2008) 29–58.
[10] P. Brockman, M. Schutte, W. Yu, Is idiosyncratic volatility priced? The international evidence. Working paper, University of Missouri-Columbia, 2007.
[11] T. Bali, N. Cakici, R. Whitelaw, Maxing out: Stock as lotteries and the cross-section of expected returns, J. Financ. Econ. 99 (2011) 427–446.
[12] K. Hou, R. Loh, Have we solved the idiosyncratic volatility puzzle? J. Financ. Econ. 121 (2016) 167–194.
[13] W. Huang, Q. Liu, G. Rhee, L. Zhang, Another look at idiosyncratic risk and expected returns. Working paper, University of Hawaii at manoa, 2007.
[14] R.D. Boehme, B.R. Danielsen, P. Kumar, S.M. Sorescu, Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets Miller (1977), J. Financ. Mark. 12 (2009) 438–468.
[15] Z. Chen, R. Petkova, Does idiosyncratic proxy for risk exposure? Rev. Financ. Stud. 25 (9) (2012) 2745–2787.
[16] Chen, G.H. Tu, H. Lin, Idiosyncratic volatility puzzle and explanations based on heterogeneous beliefs: Evidence from Chinese Stock Market. Wise Working Paper, Xiamen University, 2009 (in Chinese).
[17] G.V. Nartea, J. Wu, Z. Liu, Does idiosyncratic volatility matter in emerging markets? Evidence from China, J. Int. Financ. Mark. Inst. Money 27 (2013) 137–160.
[18] X. Deng, Z. Zheng, Is there an idiosyncratic volatility puzzle in China's Equity Market? J. Bus. Econ. 231 (1) (2011) 60–75 (in Chinese).
[19] E. Fama, K. French, A five-factor asset pricing model, J. Financ. Econ. 116 (1) (2015) 1–22.
[20] P.A. Gompers, A. Metrick, Institutional investors and equity prices, Q. J. Econ. 116 (2001) 229–259.
[21] Y. Yao, Z. Liu, A market examination of the funds' investment behavior, J. Shanxi Financ. Econ. Univ. 11 (2007) 109–113 (in Chinese).