

Hoang Van Hai

**Article**

## Firm-specific news and idiosyncratic volatility anomalies: Evidence from the Chinese stock market

Cogent Economics & Finance

**Provided in Cooperation with:**

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*Suggested Citation:* Hoang Van Hai (2022) : Firm-specific news and idiosyncratic volatility anomalies: Evidence from the Chinese stock market, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 10, Iss. 1, pp. 1-21,  
<https://doi.org/10.1080/23322039.2022.2127489>

This Version is available at:

<https://hdl.handle.net/10419/303820>

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**To cite this article:** Van Hai Hoang (2022) Firm-specific news and idiosyncratic volatility anomalies: Evidence from the Chinese stock market, Cogent Economics & Finance, 10:1, 2127489, DOI: [10.1080/23322039.2022.2127489](https://doi.org/10.1080/23322039.2022.2127489)

**To link to this article:** <https://doi.org/10.1080/23322039.2022.2127489>



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Received: 21 February 2022  
Accepted: 19 September 2022

\*Corresponding author: Van Hai Hoang, University of Economics, the University of Danang, Vietnam  
E-mail: [hoangvanhaidhkt@gmail.com](mailto:hoangvanhaidhkt@gmail.com).

Reviewing editor:  
David McMillan, Faculty of Business Administration, University of Stirling, Stirling, UK

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## FINANCIAL ECONOMICS | RESEARCH ARTICLE

# Firm-specific news and idiosyncratic volatility anomalies: Evidence from the Chinese stock market

Van Hai Hoang<sup>1\*</sup>

**Abstract:** In this paper, we examine the relationship between idiosyncratic volatility and future returns around the firm-specific news announcements in the Chinese stock market following. The results show that the pricing of non-news idiosyncratic volatility is more strongly negative compared to news idiosyncratic volatility. Such findings imply that limited arbitrage cannot fully explain the negative pricing of idiosyncratic volatility in the Chinese stock market. These results are robust after controlling for several well-known variables, such as market beta, firm size, book-to-market, momentum, liquidity, and maximum return. However, after adjusting by additional macroeconomic variables, the Chinese four-factor model and the salience trading volume factor, the average returns on zero-investment IVOL and non-news IVOL portfolios turn out to be insignificant, indicating that they may be one driver of the IVOL puzzle in the Chinese stock market.

**Subjects:** Finance; Corporate Finance; Investment & Securities; Business, Management and Accounting

### ABOUT THE AUTHOR

Van Hai Hoang is a lecturer at the University of Economics, University of Da Nang. His key research interests are on asset pricing in emerging financial markets, macroeconomics, and international economics.

### PUBLIC INTEREST STATEMENT

This study investigates the relationship between idiosyncratic volatility and future returns around the firm-specific news announcements in the Chinese stock market following DeLisle et al. (2016). The results show that the pricing of non-news idiosyncratic volatility is more strongly negative compared to news idiosyncratic volatility. Such findings imply that limited arbitrage cannot fully explain the negative pricing of idiosyncratic volatility in the Chinese stock market. These results are robust after controlling for several well-known variables, such as market beta, firm size, book-to-market, momentum, liquidity, and maximum return. However, after adjusting by additional macroeconomic variables, the Chinese four-factor model and the salience trading volume factor, the average returns on zero-investment IVOL and non-news IVOL portfolios turn out to be insignificant, indicating that they may be one driver of the IVOL puzzle in the Chinese stock market. This study contributes to a better understanding of the role of the conditional idiosyncratic volatility in asset pricing.

**Keywords:** idiosyncratic volatility; news idiosyncratic volatility; non-news idiosyncratic volatility; firm-specific news; anomalies; Chinese stock market

**JEL Classification:** Code: G11; G17; G12

## 1. Introduction

Ang et al. (2006, 2009) document a negative relationship between idiosyncratic volatility (IVOL) and subsequent stock returns in the US and other developed equity markets, which pose a challenge to the traditional asset pricing theory. Thus, many studies have been trying to solve the IVOL puzzle, such as Huang et al. (2009) within return reversal and Bali et al. (2011) within maximum return in the previous month. Recently, Stambaugh et al. (2015) argued that short-sale constraints play an important role in explaining the IVOL puzzle. This is the most promising explanation for the negative price relation, “mispricing-correction,” stemming from idiosyncratic volatility limited arbitrage. However, DeLisle et al. (2016) find evidence inconsistent with the above explanation by incorporating firm-specific news into the pricing of idiosyncratic volatility. Especially, their results are contrary to the mispricing correction hypothesis for the negative price of idiosyncratic volatility, that non-news volatility is priced more strongly than news volatility. Furthermore, the pricing of non-news volatility seems to violate the established features of the mispricing correction hypothesis. Finally, the mispricing correction hypothesis is insufficient to resolve the deep idiosyncratic volatility puzzle.

In the dimensions of the explanation of limits to arbitrage to the IVOL puzzle, the pricing power of the IVOL puzzle can be considered in four features. First, the high volatility stocks have negative risk-adjusted returns because of short selling constraints (Stambaugh et al., 2015). This statement implies that we should find a stronger negative risk-adjusted alpha in the high volatility stocks. Second, the low idiosyncratic volatility stocks should not limit arbitrageurs from correcting mispricing; therefore, they should have risk-adjusted returns of approximately zero. Third, among potentially overvalued stocks, the negative relationship between volatility and subsequent returns is particularly strong. Finally, among potentially undervalued stocks, the relation between volatility and subsequent returns is potentially positive.

The pricing of idiosyncratic volatility, by this explanation, is related to mispricing, and mispricing should be related to news. While limited arbitrage is a necessary condition for mispricing, it is not sufficient by itself. Some impetus must create a divergence of prices from fundamental values that arbitrageurs fail to expeditiously correct. Since firm-specific news moves prices, news announcements should increase the likelihood of mispricing. Idiosyncratic risk is associated with limits to arbitrage because of the difficulty in hedging positions in firms that have few close substitutes. As a result, the market has difficulty incorporating publicly available information into the stock prices of high-idiosyncratic risk firms. Consistent with this prediction, researchers have found that high-idiosyncratic risk firms exhibit stronger market anomalies; for example, studies have found that idiosyncratic securities exhibit a larger closed-end fund discount (Pontiff, 1996), a stronger S&P 500 inclusion anomaly (Wurgler & Zhuravskaya, 2002), higher returns for the book-to-market strategy (Ali et al., 2003), stronger post-earnings announcement drift (Mendenhall, 2004), and a stronger accruals anomaly (Mashruwala et al., 2006). Shleifer and Vishny (1997) present a general model of limited arbitrage, while Pontiff (2006) reviews the literature that links idiosyncratic risk and mispricing. Thus, we may expect that the four features of the pricing of idiosyncratic volatility should be strongest when volatility is contemporaneous with news announcements.

Previous literature shows that stock volatility and the macroeconomy are strongly related. Chen et al. (1986) find that the term structure spread, inflation, industrial production, and the spread of bonds are significant risk factors for the US stock market. This finding is supported by Ferson and Harvey (1991). Furthermore, Hamilton, and Susmel (1994) show that the real economic conditions significantly explained the switching from low to high volatility regimes. On the other hand,

Flannery and Protopapadakis (2002) showed that stock market returns are significantly correlated with inflation and money growth. Recently, Baker et al. (2016) link the cross-section of stock market volatility to the state of the macroeconomy as measured by the economic policy uncertainty index. The findings of the current study are consistent with those of Binder and Merges (2001) find relate stock market volatility with economic factors such as uncertainty about the price level. Bali and Zhou (2016) show that the cross-section of stock returns depends on economic uncertainty.

Motivated by these above discussions, we first examine the relationship between idiosyncratic volatility and future returns around the firm-specific news announcements in the Chinese stock market following DeLisle et al. (2016). Through such examination, we can evaluate whether the limited arbitrage explanation of the pricing of idiosyncratic volatility is sufficient. In particular, we will examine the pricing of idiosyncratic volatility, idiosyncratic volatility news, and no-news regarding the four features as mentioned above. Next, we also test whether IVOL measures are driven by some systematic variations such as macro variables. The reason we choose the Chinese stock market as a sample for our test is that Chinese market provides different empirical results in IVOL pricing context, more specifically, Chinese market is driven by individual investors, and most explanations in the US market do not apply well to the Chinese stock market (Gu et al., 2018).

To test the hypotheses empirically, we define firm-specific news as a public announcement or declaration of 1) an Announcement, 2) a CEO change, 3) an Equity structure changes, 4) External guarantee, 5) IPO, 6) Lawsuit, 7) an M&A, 8) Private placement, 9) Profit sharing-dividends payout, and 10) Public Offering, 11) Right issue, 12) Statement Release Data, and 13) Violation. Our sample data is available from 2005 to 2017. Following DeLisle et al. (2016), we decompose idiosyncratic volatility as in Ang et al. (2006) into “news idiosyncratic volatility” (IVnews) and “non-news idiosyncratic volatility” (IVnonews). The IVnews is defined as the idiosyncratic volatility around firm-specific news announcements, and the IVnonews is the idiosyncratic volatility unrelated to the firm-specific news announcements. Since firm-specific news may fluctuate stock prices, news announcements should increase the likelihood of mispricing. Thus, we expect to see a stronger effect of IVnews compared to IVnonews in the empirical test.

However, we find that IVnonews is more strongly related to future returns than the IVnews by conducting portfolio-level analysis and Fama and MacBeth (1973) regressions. The results from univariate portfolio sorting analysis show that the monthly Equal-Weighted (Value-Weighted) Fama and French (1993) three-factor alpha on the high-minus-low IVnonews portfolio is  $-0.0145$  ( $-0.0096$ ) with a Newey-West t-statistics of  $-4.61$  ( $-2.15$ ). This result is consistent with the findings of DeLisle et al. (2016) in the US market. Furthermore, this result is robust when we estimate IVOL with Fama and French (2015) five-factor model and after we control for several well-known predictors, such as market beta, book-to-market ratio, momentum, liquidity, and maximum return.

Interestingly, our results indicate that in the cross-section, the relation between idiosyncratic volatility and stock returns is positively conditional on macro factors. Portfolio analysis shows that the positive relation between expected idiosyncratic volatility and returns is economically important. We also find that IV and IVnonews are driven by Our4\_V factor model. We next investigate the interaction effect of overvaluation and news and non-news idiosyncratic volatility using a double-way sorting method. After controlling for overvaluation measures such as capital gain overhang and book-to-market ratio, the relationship between non-news IVOL and subsequent returns is still significantly and economically negative, indicating that the pricing of non-news volatility must be driven by some factor that is beyond limited arbitrage.

Our empirical results provide an important understanding of the idiosyncratic volatility puzzle on asset pricing models. First, we provide empirical evidence of the pricing of news and non-news idiosyncratic volatility in the Chinese stock market. This result is in line with the finding of DeLisle

et al. (2016) in the US market. Second, we also present evidence that limited arbitrage does not fully explain the negative relationship between IVOL and return in the Chinese stock market. Third, this paper provides an explanation of the idiosyncratic volatility puzzle by considering the link between idiosyncratic volatility and the macroeconomic variables, as well as the Our\_V factor model, which consists of first three factors in CH4 model and the salience trading volume factor proposed by Sun et al. (2022) for idiosyncratic volatility sorted portfolios in the Chinese stock market.

The remainder of this study is organized into four sections: Section 2 addresses our dataset and variable constructions; Section 3 presents the empirical test and reports the results; Section 4 concludes.

## 2. Data and Variable constructions

### 2.1. Data

We provide a thorough description of our sample that we use for this study. For the daily and monthly data, accounting data, and Fama and French (2015) five-factor data, we obtain our data from the CSMAR database. We obtain the risk-free rate and the three-factor model (Fama & French, 1993) from the RESSET database. Our sample include all of listed and delisted stocks from June 2005 to June 2017 and covers 2,676 unique stocks. The typical stock in our sample has approximately a 194-month-long time-series.

The major reason we conduct our empirical test starting from 2005 is because of the existence of News data in Chinese market. In fact, for the news data, we obtain the daily news data from RESSET database and earnings announcement dates from CSMAR Financial Database—Statements Release Dates database. The news data start from 2002 and cover market news in daily frequency, such as macro news, industrial news, and news related to individual stocks, which are collected from newswire (for example, Chinese financial news media, stock exchange news, etc.). The news related to individual stocks includes mergers and acquisitions, changes of high executives, analyst comments and rankings, insider buying and selling, significant projects, and earnings news. The earnings announcement dates data starts from year 1990 and records the release date of quarterly, semi-annual, and annual financial statements.

Before merging the news and earnings announcement dates with daily stock return data, we clean the raw data as follows. For the raw news data, we first delete the news observations that are not related to individual stocks (A-share). Then, for the cases where there are several news stories in 1 day for the same stock, we delete the duplicates and keep only one firm-date observation for each stock in each trading day. Table 1 and reports the number of observations for news data.

From Table 1, we can find that the number of observations is few before year 2005. Therefore, for the test relative to the news and IVOL in our sample, the sample is selected from 2005.

In order to maximize the economic and practical significance of our results, we include the following filters on our sample of stocks. First, we require that the stocks have available data for all of the standard and idiosyncratic volatility-specific controls. In addition, we exclude firms in financial sector and firms under special treatment.<sup>1</sup> Finally, we exclude all of the stocks with a (unadjusted) price less than ¥1 (Chinese Yuan RMB) and firms with negative book value of equity. We exclude all stocks that traded fewer than 15 trading days during month  $t-1$ . Given these filters, we are confident that our results will have practical significance in addition to economic and statistical significance.

### 2.2. Variable constructions

Firstly, we estimate the idiosyncratic volatility (IVOL). Following Ang et al. (2006), idiosyncratic volatility (IVOL) is defined as the standard deviation of daily residuals relative to Fama and French

**Table 1. Number of public news observation in the Chinese stock market**

Year	Raw data	News related to A-share	After excluding duplications (for each stock, only keep one news observations each day)	After excluding financial firms
2002	264	119	113	102
2003	369	125	119	105
2004	245	134	125	109
<b>2005</b>	<b>669</b>	<b>385</b>	<b>366</b>	<b>352</b>
2006	748	317	312	302
2007	704	393	383	366
2008	210,032	43,939	29,746	27,136
2009	197,420	38,141	26,863	24,591
2010	247,973	41,451	27,820	25,348
2011	296,640	45,404	29,756	26,903
2012	429,696	81,518	52,885	47,091
2013	667,880	120,871	66,269	60,406
2014	951,048	152,381	78,216	71,471
2015	946,747	215,949	107,198	98,535
2016	932,141	347,752	171,650	160,072
2017	452,189	191,522	111,254	102,212

(1993) three-factor over the previous month. Following DeLisle et al. (2016), the IVOL is modified by multiplying the square root of 30 in order to convert the daily estimate of idiosyncratic volatility to a monthly quantity (i.e., 30 days). Specifically speaking, the monthly IVOL is estimated as follows: every month we conduct the following regression for each stock:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_1 \text{RMRF}_d + \beta_2 \text{SMB}_d + \beta_3 \text{HML}_d + \epsilon_{i,d} \quad (1)$$

where  $R_{i,d}$  is stock  $i$ 's daily return on day  $d$ ,  $R_{f,d}$  is the risk-free rate on day  $d$ , and  $\epsilon_{i,d}$  is the daily residuals of stock  $i$  on day  $d$  relative to Fama and French (1993) three-factor.

Following DeLisle et al. (2016), the stock  $i$ 's idiosyncratic volatility in month  $t$  is estimated as:

$$IV_{i,t} = \sqrt{\frac{30}{D_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} \epsilon_{i,d}^2} \quad (2)$$

where  $D_{i,t}$  is the number of normal trading days for stock  $i$  in month  $t$  and  $\epsilon_{i,d}^2$  is the square of the daily residual estimated from equation (1). We require at least 15 normal trading days in month  $t$  to estimate the monthly idiosyncratic volatility.

Following DeLisle et al. (2016), we then incorporate firm-specific news into the pricing of idiosyncratic volatility and decompose the volatility into news and non-news volatility by modifying equation (2) as follows:



$$IVnews_{i,t} = \sqrt{\frac{30}{N_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} (\eta_{i,d} \times \epsilon_{i,d}^2)} \quad (3)$$

$$IVnonews_{i,t} = \sqrt{\frac{30}{D_{i,t} - N_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} ((1 - \eta_{i,d}) \times \epsilon_{i,d}^2)} \quad (4)$$

where  $N_{i,t}$  is the number of normal trading days during month  $t$  on which a firm-specific news announcement occurs,  $\eta_{i,d}$  is an indicator variable that equals to 1 if there is a firm-specific news announcement on day  $d$  and zero, otherwise. Since we employ a four-day window around the reported announcement date,  $N_{i,t}$  is typically a multiple of four except for the case where a news announcement is made on the first or last day of a calendar month. More specifically, if a firm-specific news announcement was made on day  $d$  for stock  $i$ , then the days from  $d - 4$  to  $d + 4$  over month  $t$  are defined as event dates, where  $\eta_{i,d}$  are set equal to 1.

We identify 13 types of firm-specific news from several different publicly available corporate event databases that are obtained from the CSMAR database. We define firm-specific news as a public announcement or declaration of 1) an Announcement, 2) a CEO change, 3) an Equity structure changes, 4) External guarantee, 5) IPO, 6) Lawsuit, 7) an M&A, 8) Private placement, 9) Profit sharing-dividends payout, and 10) Public Offering, 11) Right issue, 12) Statement Release Data, and 13) Violation. Our sample data is available from 2005 to 2017. The macro variables include five proxies: Industrial Added Value, Consumer Price Index, Producer Price Index, Macro-Economic Climate Index, and Manufacturing Purchasing Managers' Index (He et al., 2017).

For other controlling variables, we include as a set of standard control variables: market beta, size, and book-to-market ratio following Fama and French (1993), momentum returns (the cumulative return over months  $t-12$  to  $t-2$ ), the turnover following Han and Lesmond (2011), the return reversal following Huang et al. (2010), and the maximum daily return during month  $t-1$  following Bali et al. (2011). We also use the book-to-market ratio (Fama & French, 1993) and capital gains overhang (Bhootra & Hur, 2015) as our measures of overvaluation. See Appendix A for details concerning the construction of these variables.

In Table 2, we present the time-series average of cross-sectional statistics of idiosyncratic volatility (IVOL), news idiosyncratic volatility (IVnews) and non-news idiosyncratic volatility (IVnonews). In each month, we compute the mean, standard deviation, median, Q1, and Q3 for the volatility measures. We then average those five statistics across cross-sections.

In this table, we report the grand averages of several summary statistics our main idiosyncratic volatility estimates. We calculate the summary statistics of idiosyncratic volatility (IVOL), news idiosyncratic volatility (IVnews), and non-news idiosyncratic volatility (IVnonews). We compute the summary statistics for each monthly cross-section in our sample and then calculate the equal-weighted average of these statistics. For this table, we only include the firm-months that had a firm-specific news announcement the previous month. Due to data requirements and availability, our sample is from July 2005-June 2017.

**Table 2. Summary statistics**

Variable	Mean	Std Dev	Median	Q1	Q3
IVOL	0.1333	0.1125	0.1218	0.0886	0.1644
IVnews	0.1321	0.1698	0.1174	0.0816	0.1666
IVnonews	0.1205	0.1027	0.1082	0.0846	0.1626



From Table 2, we find that news volatility is higher and more dispersed across stocks than non-news volatility. The time-series mean of cross-sectional news volatility is 0.1321, and of non-news volatility is 0.1205. While the average news and non-news volatilities of the typical cross-section are similar in magnitude, the dispersions are not. The standard deviation of news volatility in the typical cross-section is 0.1698, while it is only 0.1027 for non-news volatility.

### 3. Results and discussion

#### 3.1. Pricing of news and non-news idiosyncratic volatility

##### 3.1.1. Univariate portfolio sort

DeLisle et al. (2016) find evidence inconsistent with the explanation by incorporating firm-specific news into the pricing of idiosyncratic volatility in the US stock market. Especially, their results are contrary to the mispricing correction hypothesis for the negative price of IV, that IVnonews is priced more strongly than IVnews. Furthermore, the pricing of IVnonews seems to violate the established features of the mispricing correction hypothesis. Thus, they conclude that the mispricing correction hypothesis is insufficient to resolve the deep idiosyncratic volatility puzzle.

Following DeLisle et al. (2016), in this study, we evaluate the limited arbitrage explanation of the pricing of idiosyncratic volatility by examining actual firm-specific news announcements. We first conduct portfolio-level analysis to investigate the relationship between the idiosyncratic volatility (IVOL; as in Ang et al., 2006), news idiosyncratic volatility (IVnews), and non-news idiosyncratic volatility (IVnonews; as in DeLisle et al., 2016) in the Chinese stock market. IVnews is the idiosyncratic volatility related to firm-specific news announcements. IVnonews is the idiosyncratic volatility unrelated to news announcements. At the beginning of each month  $t-1$ , we sort stocks into quintiles based on their idiosyncratic volatility, news volatility, or non-news volatility. We then hold these quintile portfolios over month  $t$  and estimate the average portfolio returns and Fama and French (1993) three-factor alphas in month  $t$  on equal-weighted (EW) and value-weighted (VW) basis. We also form a zero-cost portfolio that is short for the lowest quintile portfolio and long for the highest quintile portfolio. We then estimate the time-series average of monthly returns and Fama and French (1993) three-factor alphas.

Table 3 shows the results of the value-weighted (VW) and equal-weighted (EW) returns on portfolios sorted based on our idiosyncratic volatility (IVOL in Panel A, IVnews in Panel B, and IVnonews in Panel C). In the rightmost column, we show a zero-investment portfolio return that is long the quintile of stocks with the highest idiosyncratic volatility and short the quintile of stocks with the lowest idiosyncratic volatility. Newey and West (1987) adjusted  $t$ -statistic is reported in parentheses.

In this table, we report the average returns and Fama and French (1993) three-factor alphas for idiosyncratic volatility sorted portfolios. In Panel A, we form portfolios based on idiosyncratic volatility. In Panel B (Panel C), we form portfolios based on news (non-news) idiosyncratic volatility. In each month, we sort all stocks into quintiles based on their idiosyncratic volatility in the last month and hold the portfolio for month  $t$ . Finally, we report the average return and alphas in both equal weighting (EW) and value weighting (VW) portfolio schemes. In the (H-L) column, the return is for a zero-investment portfolio that is long the quintile of stocks with the highest idiosyncratic volatility and short the quintile of stocks with the lowest idiosyncratic volatility. Our sample is from June 2005 to June 2017. Robust Newey-West  $t$ -statistics (estimated with four lags) are given in parentheses. We denote statistical significance at the 1%, 5%, and 10% levels with \*\*\*, \*\*, and \*, respectively.

In panel A, we present the EW and VW returns of portfolios sorted on idiosyncratic volatility (IVOL). The returns are roughly decreasing in IVOL in both the VW and EW portfolios. The average return (FF3 alpha) on the EW H-L portfolio is  $-0.0187$  ( $-0.0144$ ) and significant at the 1% level, and

**Table 3. Return on portfolios sorted on news and non-news idiosyncratic volatility**

		L	2	3	4	H	H-L
<b>Panel A: Idiosyncratic Volatility—IV</b>							
EW	Average return	0.0306** (2.38)	0.0286** (2.29)	0.0270** (2.13)	0.0235* (1.88)	0.0119 (1.02)	-0.0187*** (-5.99)
	FF3 Alpha	0.0034 (1.52)	0.0017 (1.16)	0.0006 (0.36)	-0.0023 (-1.55)	-0.0110*** (-6.19)	-0.0144*** (-4.72)
VW	Average return	0.0184 (1.49)	0.0174 (1.41)	0.0165 (1.32)	0.0158 (1.24)	0.0074 (0.60)	-0.0110** (-2.36)
	FF3 Alpha	-0.0005 (-0.19)	-0.0005 (-0.18)	0.0023 (0.97)	-0.0001 (-0.01)	-0.0092*** (-3.28)	-0.0088** (-2.03)
<b>Panel B: News Idiosyncratic Volatility—IVNEWS</b>							
EW	Average return	0.0400*** (2.83)	0.0290* (1.94)	0.0355*** (2.63)	0.0374** (2.26)	0.0365** (2.38)	-0.0019 (-0.20)
	FF3 Alpha	0.0110** (2.48)	0.0006 (0.12)	0.0031 (0.35)	0.0159** (1.99)	0.0128 (1.29)	0.0028 (0.25)
VW	Average return	0.0299** (2.39)	0.0222 (1.52)	0.0289** (2.16)	0.0243 (1.53)	0.0269* (1.95)	-0.0015 (-0.14)
	FF3 Alpha	0.0045 (1.13)	0.0015 (0.26)	0.0012 (0.13)	0.0077 (0.95)	0.0068 (0.71)	0.0031 (0.27)
<b>Panel C: Non-News Idiosyncratic Volatility—IVNONEWS</b>							
EW	Average return	0.0311** (2.38)	0.0292** (2.32)	0.0274 (2.15)	0.0239* (1.89)	0.0125 (1.05)	-0.0186*** (-5.89)
	FF3 Alpha	0.0042** (1.98)	0.0022 (1.28)	0.0013 (0.77)	-0.0020 (-1.38)	-0.0103*** (-5.85)	-0.0145*** (-4.61)
VW	Average return	0.0191** (1.99)	0.0173 (1.40)	0.0174 (1.36)	0.0155 (1.22)	0.0074 (0.59)	-0.0117** (-2.49)
	FF3 Alpha	0.0007** (2.26)	-0.0004 (-0.14)	0.0027 (1.06)	-0.0001 (-0.02)	-0.0089*** (-3.21)	-0.0096** (-2.15)

the return (FF3 alpha) on the VW H-L portfolio is -0.0110 (-0.0088) and significant at the 1% level. Thus, we can confirm the existence of the negative relationship between IV and future returns in the Chinese market by using our sample data. This result is consistent with those from Nartea et al. (2017), Wan (2018).

In panel B of Table 3, we sort stocks into quintiles based on news idiosyncratic volatility (IVnews). The average portfolio returns are fluctuant in idiosyncratic volatility for both VW and EW portfolios. The return (FF3 alpha) on the EW H-L portfolio is -0.0019 (0.0028) and statistical insignificant with t-statistic of -0.20 (0.25). The return (FF3 alpha) VW H-L portfolio is only -0.0015 (0.0031), which is not statistically significant. In Panel C, as we expected, the returns are monotonically decreasing in idiosyncratic volatility (IVnonews) for both the EW and VW portfolios. The EW H-L portfolio return (FF3 alpha) is -0.0186 (-0.0145) and significant at the 1% level, while the VW H-L portfolio returns (FF3 alpha) is -0.0117 (-0.0096) and significant at the 5% level. The negative relation found in Ang et al. (2006) is robust to VW and EW portfolio returns based on idiosyncratic volatility (IVnonews) in the Chinese stock market.

Based on prior experimental evidence, we posit that if the idiosyncratic volatility only affects asset prices as a limit of arbitrage, the pricing of IVnews should be stronger than the pricing of IVnonews. However, from the results of Panel A, Panel B, and Panel C, it can be seen that IVnonews is more strongly related to future returns than the IVnews. Further, the returns in the high IVnonews portfolio are strongly negative. In contrast, the return in the low IVnonews is positively significant. This result is not consistent with the limits of arbitrage explanation. Thus, the evidence supports the conclusion that limited arbitrage does not fully explain the negative price of idiosyncratic volatility. Consequently,

we believe that our study extends the contributions from previous studies, such as Bali et al. (2011) and DeLisle et al. (2016), in investigating the pricing of idiosyncratic volatility.

### 3.1.2. Firm-level cross-sectional regressions

So far, we have already observed the firm-specific news effect on the pricing of idiosyncratic volatility in Chinese stock market by using single portfolio sort method. However, as Fama and French (2008) point out, portfolio tests are limited by the number of control variables at one time. Therefore, as a robustness test, we perform Fama and MacBeth (1973) cross-sectional regressions that are necessary to control a large set of potential covariates. By doing this test, we can reexamine the pricing of news and non-news idiosyncratic volatility in the firm-level regression, as well as control other well-known variables which can affect the pricing of news and non-news idiosyncratic volatility in the cross-section of stock returns. The control variables include size, book-to-market ratio (Fama & French, 1993), return reversals (Huang et al., 2010), momentum, turnover (Chordia et al., 2001), and maximum return (Bali et al., 2011).

In Table 4, we show the results in the cross-sectional regressions that are similar to Fama and MacBeth (1973), including idiosyncratic volatility (IVOL) and news idiosyncratic volatility (IVnews) and non-news idiosyncratic volatility (IVnonews). Models 1 and 2 are regression models with idiosyncratic volatility and other control variables. Models 3 and 4 are regressions with news idiosyncratic volatility and other control variables. Models 5 and 6 are regressions with non-news idiosyncratic volatility and other control variables. Finally, Models 7 and 8 are regressions with both news and non-news idiosyncratic volatility and other control variables. Specifically speaking, each month we perform the following Fama and MacBeth (1973) regressions with different firm characteristics included as control variables:

$$R_{i,t+1} = \alpha_0 + \beta_{IV} IV_{i,t} + \beta_{IVnews} IVnews_{i,t} + \beta_{IVnonews} IVnonews_{i,t} + \beta_{X_n} X_{i,n,t} + \epsilon_{i,t+1} \quad (5)$$

where  $R_{i,t+1}$  is the realized return on stock  $i$  in month  $t + 1$ .  $IVOL_{i,t}$  is the idiosyncratic volatility.  $IVnews_{i,t}$  ( $IVnonews_{i,t}$ ) is the news (non-news) idiosyncratic volatility of stock  $i$  in month  $t$ .  $X_{i,n,t}$  is the set of control variables, including firm size (SIZE), market beta (BETA), book-to-market (BM), short-term reversal (REV), momentum (MOM), liquidity (LIQ), and maximum return (MAX). The results are present in Table 4.

In this table, we present the coefficient estimates and t-statistics from the Fama and MacBeth (1973) cross-sectional regressions of individual stock excess returns, on the listed variables. Models 1 and 2 are regression models with idiosyncratic volatility and other control variables. Models 3 and 4 are regression models with news idiosyncratic volatility and other control variables. Models 5 and 6 are regression models with non-news idiosyncratic volatility and other control variables. Finally, Models 7 and 8 are regression models with both news and non-news idiosyncratic volatility and other control variables. See more detail for variable construction in Appendix A. Our sample is from June 2005 to June 2017. Robust Newey–West t-statistics (estimated with four lags) are given in parentheses. We denote statistical significance at the 1%, 5%, and 10% levels with \*\*\*, \*\*, and \*, respectively.

In Model 1, the average slope of IVOL is  $-0.1414$  with a Newey–West t-statistics of  $-7.40$ . The average slope of IVOL remains negative and statistically significant in Model 2, indicating that none of the control variables can explain the IVOL anomaly individually, which is consistent with previous studies such as Bali et al. (2011), Annaert et al. (2013), Walkshäusl (2014), and Wan (2018). When we move to the IVnews in the Model 3 (Model 4), the average slope of IVnews is  $0.0329$  ( $-0.0633$ ) with a Newey–West t-statistics of  $0.79$  ( $-0.29$ ), indicating that there is no evidence of the predictive power of stock returns by IVnews in the Chinese stock market.

**Table 4. The pricing of news and non-news idiosyncratic volatility in cross-sectional regressions**

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8
IV	-0.1414*** (-7.40)	-0.1486*** (-4.92)						
IV_NEWS			0.0329 (0.79)	-0.0633 (-0.29)			0.0355* (1.83)	0.0423** (2.20)
IV_NONEWS					-0.1345*** (-6.97)	-0.1214*** (-4.79)	-0.1192*** (-0.704)	-0.1043*** (-4.50)
BETA		-0.0004 (-0.22)		0.1172 (0.82)		-0.0010 (-0.58)		-0.0008 (-0.44)
SIZE		-0.0089*** (-5.31)		-0.0005 (-0.04)		-0.0088*** (-5.06)		-0.0087*** (-5.17)
BM		-0.0003 (-0.21)		0.0149 (1.15)		-0.0001 (-0.06)		0.0004 (0.27)
MOM		-0.0019 (-0.39)		0.0293 (1.57)		-0.0022 (-0.41)		-0.0026 (-0.53)
REV		0.0557*** (3.08)		0.0634** (2.28)		0.0575*** (3.14)		0.0699** (2.58)
LIQ		-0.0047*** (-3.39)		0.0021 (0.18)		-0.0048*** (-3.51)		-0.0048*** (-3.61)
MAX		-0.0052 (-0.11)		0.2921 (0.97)		-0.0589* (-1.82)		-0.0774** (-2.22)

From Model 5 and Model 6, we examine the relationship between IVnonews and future returns; it can be seen that there is an economically and statistically significant negative relation between non-news idiosyncratic volatility and future stock returns in the Chinese stock market, which is consistent with the findings on the US markets in DeLisle et al. (2016). From Model 7, and Model 8, when we include IVnews and IVnonews together in the regression model, the IVnews become positive and significant at 10% in Model 7 and 5% in Model 8. In addition, the prediction power of IVnonews remains negative and significant at conventional level. Particularly, the coefficient of IVnonews is -0.1191 with a t-statistics of -7.04 in Model 7, and the coefficient is -0.1043 with a t-statistics of -4.50 in model 8. Thus, this result implies that IVnonews cannot be eliminated by other variables in Chinese stock market. Finally, we conclude that the negative relation between IVOL following Ang et al. (2006), as well as IVnonews following DeLisle et al. (2016) and subsequent returns in the Chinese stock market.

### 3.2. Additional test

#### 3.2.1. Seasonality in pricing of non-news idiosyncratic volatility

Following Peterson and Smedema (2011) indicated that the relation between IVOL and future return is stronger in non-January data, when January data is excluded from the sample. So, in this part, we directly investigate the impact of seasonality on the relationship between IVnonews and return in the Chinese stock market. We provide the results of a portfolio-level analysis in Table 5.

We first construct time-series portfolios to address the impact of seasonality and robustness of the negative IVnonews and return relation. At the beginning of each month, we use an IVnonews measure to sort stocks into quintiles. We calculate and test the significance of the value-weighted (hereafter VW) and equal-weighted (hereafter EW) portfolio returns. Furthermore, we construct zero-investment “high minus low” (hereafter H-L) portfolios by buying the portfolio of stocks in the highest idiosyncratic volatility quintile and shorting the stocks in the lowest idiosyncratic volatility quintile. We address the seasonality by calculating the average returns in January only in Panel A, and in non-January months in Panel B.

**Table 5. Seasonality return of portfolios sorted on non-news idiosyncratic volatility**

		L	2	3	4	H	H-L
<b>Panel A: January—IVnonews</b>							
EW	Average return	0.0157 (0.41)	0.0128 (0.33)	0.0103 (0.28)	0.0060 (0.16)	-0.0074 (-0.23)	-0.0231** (-2.09)
	FF3 Alpha	0.0098 (1.05)	0.0082 (0.73)	0.0102 (1.48)	0.0060 (1.02)	-0.0036 (-1.15)	-0.0134 (-1.33)
VW	Average return	0.0068 (0.23)	-0.0065 (-0.21)	-0.0154 (-0.57)	-0.0103 (-0.29)	-0.0345 (-1.17)	-0.0413*** (-3.73)
	FF3 Alpha	0.0173 (1.64)	0.0177 (1.04)	0.0078 (1.01)	-0.0017 (-0.22)	-0.0193 (-2.89)	-0.0366** (-2.43)
<b>Panel B: Non January—IVnonews</b>							
EW	Average return	0.0324*** (2.72)	0.0306*** (2.66)	0.0289** (2.43)	0.0254 (2.13)	0.0142 (1.24)	-0.0182*** (-5.62)
	FF3 Alpha	0.0033 (1.24)	0.0015 (0.69)	0.0004 (0.18)	-0.0030 (-1.56)	-0.0112*** (-5.20)	-0.0145*** (-4.85)
VW	Average return	0.0201* (1.83)	0.0194* (1.76)	0.0202* (1.77)	0.0177 (1.55)	0.0110 (0.89)	-0.0091** (-2.05)
	FF3 Alpha	-0.0009 (-0.35)	-0.0010 (-0.32)	0.0024 (0.84)	-0.0007 (-0.28)	-0.0087** (-2.48)	-0.0078** (-2.18)

In this table, we report the average returns and Fama and French (1993) three-factor alphas for non-news idiosyncratic volatility sorted portfolios. In Panel A (Panel B), we form portfolios based on non-news idiosyncratic volatility in January (Non-January). In each month, we sort all stocks into quintiles based on their idiosyncratic volatility in the last month and hold the portfolio for month  $t$ . Finally, we report the average return and alphas in both equal weighting (EW) and value weighting (VW) portfolio scheme. In the (H-L) column, the return is for a zero-investment portfolio that is long the quintile of stocks with the highest idiosyncratic volatility and short the quintile of stocks with the lowest idiosyncratic volatility. Our sample is from June 2005 to June 2017. Robust Newey-West  $t$ -statistics (estimated with four lags) are given in parentheses. We denote statistical significance at the 1%, 5%, and 10% levels with \*\*\*, \*\*, and \*, respectively.

In panel A, the stock samples are sorted based on IVnonews over the previous month. We then calculate the VW and EW returns on these portfolios and an H-L portfolio. For January, though, the portfolio returns are perfectly monotonically decreasing in idiosyncratic volatility. Both the VW and EW H-L portfolio returns are negative and significant, expected EW FF3 alpha return. The return on the EW (VW) H-L portfolio is -0.0231 (-0.0413) and significant at the 5% level (1% level), while the return on the EW (VW) FF3 portfolio is -0.0134 (-0.0366) with a  $t$ -statistics of -1.33 (-2.43).

In Panel B, we expect a stronger negative relation between idiosyncratic volatility and returns when excluding January. We find returns approximately decreasing in idiosyncratic volatility for both the VW and EW portfolios. The EW (VW) H-L portfolio return is -0.0182 (-5.62) and significant at the 1% (5%) level, while the EW (VW) FF3 alpha portfolio return is -0.145 (-0.0078) and significant at the 1% (5%) level. Clearly, the negative relation IVnonews and return is strong and robust to value weighting and equal weighting both in and outside of January. Thus, we cannot dismiss the negative relation, as it seems robust. In general, these above results are consistent with Peterson and Smedema (2011) for idiosyncratic volatility analysis, and DeLisle et al. (2016) for non-news idiosyncratic volatility in the US market.

### 3.2.2. Pricing of news and non-news idiosyncratic volatility after controlling for alternative models

Ang et al. (2009) propose that the IV could be explained by a missing risk factor. Therefore, in this part, we investigate the ability of recent models to explain the IV, such as Fama and French (2015)

five-factor model, the Chinese four-factor (CH4) model proposed by Liu et al. (2019), and the Our4\_V model proposed by Sun et al. (2022). Besides, the relationship between stock volatility and the macroeconomy has been well documented in previous studies such as Chen et al. (1986), Schwert (1989), and Baker et al. (2016). Recently, Cheon and Lee (2018) also utilize the macro variables to control the MAX effect in the Korean stock market. In this study, we follow the procedure of Cheon and Lee (2018) to estimate the risk-adjusted returns relative to Fama and French (1993) three factors in addition to macroeconomic factors in the Chinese stock market. In other words, macro variables are used with the Fama–French factors in the regression model. The time-varying loadings on these risk macro factors are detailed in Appendix B. The results are provided in Table 6.

In this table, we report the average returns and Fama and French (1993) five-factor alphas, macro variables, Chinese four-factor (CH4), and Our4\_V (consist of first three factors in CH4 model and the salience trading volume factor for idiosyncratic volatility sorted portfolios) for idiosyncratic volatility sorted portfolios. In Panel A, we form portfolios based on idiosyncratic volatility. In Panel B (Panel C), we form portfolios based on news (non-news) idiosyncratic volatility. In each month, we sort all stocks into quintiles based on their idiosyncratic volatility in the last month and hold the portfolio for month  $t$ . Finally, we report the average return and alphas in both equal weighting (EW) and value weighting (VW) portfolio scheme. In the (H–L) column, the return is for a zero-investment portfolio that is long the quintile of stocks with the highest idiosyncratic volatility and short the quintile of stocks with the lowest idiosyncratic volatility. Our sample is from June 2005 to June 2017. Robust Newey–West  $t$ -statistics (estimated with four lags) are given in parentheses. We denote statistical significance at the 1%, 5%, and 10% levels with \*\*\*, \*\*, and \*, respectively.

First, when we use Fama and French (2015) five-factor model, our portfolio alphas are statistically and economically significant when forming portfolios on IV, IVnonews, but insignificant for IVnews. For example, the IV return on the EW (VW) Ave H–L portfolio is  $-0.0184$  ( $-0.0101$ ) and significant at 1% (10%) level, while the IV return on the EW (VW) Alpha H–L portfolio is  $-0.0154$  ( $-0.0108$ ) with a  $t$ -statistics of  $-5.66$  ( $-1.66$ ). These results can also be found in the IVnonews portfolio in Panel C. This result is almost the same as Table 3 results and is consistent with Annaert et al. (2013) and Walkshäusl (2014) for emerging market and DeLisle et al. (2016) for the US market.

This result implies that when IV and IVnonews are not conditioned on the macro factors, the relation turns strongly negative, implying that investors are not compensated for taking on additional risk, rather the opposite, i.e., the idiosyncratic volatility puzzle. Note that the finding without macro factors is consistent with the findings in Ang et al. (2006, 2009). However, for the idiosyncratic volatility based on macro factors, the returns on the hedge portfolios are statistically insignificant. For example, the IV return on the EW (VW) Macro H–L portfolio is  $-0.0229$  ( $0.4021$ ) and insignificant, while the IVnonews return on the EW (VW) Macro H–L portfolio is  $-0.2391$  ( $0.4113$ ) with a  $t$ -statistics of  $-1.26$  ( $1.22$ ). This result suggests that macroeconomic factors may play a critical role in the pricing of IVOL in the Chinese stock market. This result is consistent with the findings of Goyal and Welch (2008).

When we move on to the CH4 results, it can be seen that IV and IVnonews still exist in the EW portfolios. Particularly, in Panel A (Panel C), the CH4 alpha on the EW H–L portfolio is  $-0.0132$  ( $-0.0116$ ) and statistically significant with a  $t$ -statistic of  $-2.77$  ( $-2.64$ ), while the VW H–L portfolio is  $-0.0071$  ( $-0.0076$ ) and statistical insignificant with  $t$ -statistic of  $-1.27$  ( $-1.29$ ). This result suggests that IV only exists in the EW portfolio returns after controlling the CH4 factor model.

Interestingly, we find that IVOL can be explained by the Our4\_V factor model. In particular, in Panel A for IV, the Our4\_V alpha on the EW H–L portfolio (VW H–L portfolios) is  $-0.0104$  ( $-0.0035$ ) and statistically insignificant with a  $t$ -statistic of  $-1.62$  ( $-0.53$ ). In Panel C for IVnonews, the Our4\_V

**Table 6. Return on portfolios sorted on news and non-news idiosyncratic volatility for alternative models**

		L	2	3	4	H	H-L
<b>Panel A: Idiosyncratic Volatility—IV</b>							
EW	Average return	0.0311*** (2.65)	0.0302*** (2.61)	0.0280** (2.40)	0.0238** (2.02)	0.0127 (1.12)	-0.0184*** (-6.33)
	FF5 Alpha	0.0046* (1.93)	0.0034* (1.66)	0.0017 (0.89)	-0.0020 (-1.01)	-0.0108*** (-5.30)	-0.0154*** (-5.66)
	Macro	0.1546 (0.90)	0.0885 (0.59)	0.1084 (0.68)	0.0268 (0.17)	-0.0683 (-0.34)	-0.2229 (-1.24)
	CH4	0.0074*** (2.67)	0.0049** (2.55)	0.0047*** (3.21)	0.0023*** (2.69)	-0.0058** (-2.54)	-0.0132*** (-2.77)
	Our4_V	0.0047 (1.56)	0.0028 (1.28)	0.0024 (1.44)	0.0005 (0.30)	-0.0057* (-1.67)	-0.0104 (-1.62)
VW	Average return	0.0185* (1.80)	0.0203* (1.81)	0.0188* (1.67)	0.0157 (1.35)	0.0084 (0.69)	-0.0101* (-1.92)
	FF5 Alpha	0.0019 (0.69)	0.0042 (1.48)	0.0014 (0.54)	-0.0006 (-0.21)	-0.0089** (-2.21)	-0.0108* (-1.66)
	Macro	-0.1093 (-0.59)	-0.1655 (-1.08)	-0.1805 (-0.98)	-0.0658 (-0.38)	0.2928 (1.24)	0.4021 (1.10)
	CH4	0.0026 (0.77)	-0.0011 (-0.42)	0.0014 (0.58)	-0.0016 (-0.92)	-0.0045 (-1.52)	-0.0071 (-1.27)
	Our4_V	0.0005 (0.19)	-0.0015 (-0.57)	0.0017 (0.64)	-0.0025 (-1.19)	-0.0030 (-0.75)	-0.0035 (-0.53)
<b>Panel B: News Idiosyncratic Volatility—IVNEWS</b>							
EW	Average return	0.0444*** (3.10)	0.0508*** (3.22)	0.0333* (1.83)	0.0384** (2.18)	0.0454*** (2.97)	0.0001 (0.65)
	FF5 Alpha	0.0218 (1.62)	0.0319*** (3.08)	0.0087 (0.81)	0.0178 (1.24)	0.0170** (2.02)	-0.0048 (0.34)
	Macro	0.9231*** (3.17)	-0.9623 (-1.28)	-0.7815* (-1.93)	0.1724 (0.26)	0.2540 (0.65)	0.1010 (0.17)
	CH4	0.0094** (2.35)	0.0137** (2.13)	0.0232** (2.34)	0.0063 (0.53)	0.0101 (1.14)	0.0007 (0.53)
	Our4_V	0.0058 (1.21)	0.0165* (1.69)	0.0263** (2.00)	0.0033 (0.22)	0.0109 (1.04)	0.0051 (0.86)
VW	Average return	0.0310** (2.33)	0.0406*** (2.87)	0.0230 (1.31)	0.0274 (1.52)	0.0314** (2.17)	0.0004 (0.55)
	FF5 Alpha	0.0135 (1.02)	0.0288*** (3.25)	0.0057 (0.50)	0.0110 (0.77)	0.0056 (0.62)	-0.0079 (0.15)
	Macro	0.9613*** (3.13)	-0.8513 (-1.33)	-0.8061** (-1.98)	-0.2463 (-0.41)	0.2570 (0.57)	0.0979 (0.16)
	CH4	0.0022 (0.55)	0.0060 (1.02)	0.0200** (2.11)	0.0034 (0.30)	-0.0017 (-0.15)	-0.0039 (0.16)
	Our4_V	-0.0015 (-0.39)	0.0083 (0.95)	0.0246** (1.96)	0.0059 (0.52)	-0.0009 (-0.07)	0.0006 (0.47)

(Continued)



**Table 6. (Continued)**

		L	2	3	4	H	H-L
<b>Panel C: Non-News Idiosyncratic Volatility—IVNONEWS</b>							
EW	Average return	0.0300** (2.53)	0.0299** (2.54)	0.0273** (2.32)	0.0242 (2.05)	0.0127 (1.12)	-0.0173*** (-5.74)
	FF5 Alpha	0.0037 (1.43)	0.0032 (1.42)	0.0010 (0.51)	-0.0017 (-0.87)	-0.0107*** (-5.35)	-0.0144*** (-4.96)
	Macro	0.1895 (1.13)	0.0854 (0.53)	0.1172 (0.72)	-0.0079 (-0.05)	-0.0496 (-0.24)	-0.2391 (-1.26)
	CH4	0.0059** (2.14)	0.0047** (2.37)	0.0037*** (2.95)	0.0019 (1.64)	-0.0057*** (-3.04)	-0.0116*** (-2.64)
	Our4_V	0.0033 (1.14)	0.0027 (1.13)	0.0015 (0.87)	-0.0002 (-0.12)	-0.0058** (-1.89)	-0.0091 (-1.47)
VW	Average return	0.0186* (1.78)	0.0193* (1.71)	0.0175 (1.59)	0.0163 (1.38)	0.0079 (0.66)	-0.0107** (-2.10)
	FF5 Alpha	0.0022 (0.80)	0.0021 (0.76)	0.0026 (1.01)	-0.0007 (-0.21)	-0.0088** (-2.39)	-0.0110* (-1.79)
	Macro	-0.0697 (-0.40)	-0.1450 (-0.79)	-0.1280 (-0.77)	-0.1701 (-0.92)	0.3417 (1.56)	0.4113 (1.22)
	CH4	0.0024 (0.72)	-0.0020 (-0.76)	0.0006 (0.26)	-0.0020 (-1.10)	-0.0052* (-1.76)	-0.0076 (-1.29)
	Our4_V	0.0006 (0.16)	-0.0024 (-0.84)	0.0002 (0.07)	-0.0026 (-1.26)	-0.0036 (-0.89)	-0.0042 (-0.61)

alpha on the EW H-L portfolio (VW H-L portfolios) is -0.0091 (-0.0042) and statistically insignificant with a t-statistic of -1.47 (-0.61). These results indicate that IV and IVnonews are driven by the Our4\_V factor model.

From the results of Panel A and Panel C, it can be seen that the results of IV and IVnonews are similarly priced features. Especially, the returns in the high IV and IVnonews portfolios are strongly negative. In contrast, the returns in the low IV and IVnonews are positive and insignificant. These results are consistent with our hypothesis, which is mentioned in the introduction part. Regarding IVnews, the results in Panel B indicate that IVnews is not priced. This result is not consistent with the limits of arbitrage explanation.

### 3.2.3. Idiosyncratic volatility and overvaluation

Previous research has shown that the negative price of idiosyncratic volatility is only found in stocks with high overvaluation. This is in line with the argument that limits to arbitrage induce overvaluation and make arbitrage become riskier (Gu et al.). Thus, in this part, we examine the effect of overvaluation on news and non-news volatility. Moreover, extant literature indicates that stocks with low book-to-market ratio (Ali et al., 2003) and capital gains overhang (Bhootha & Hur, 2015) are, on average, overvalued and experience low future returns. Thus, we use the book-to-market ratio, and the net capital gains overhang as measures of overvaluation in this study.

To empirically analyze the relations, following Bali et al. (2011), we first sort the stocks into quintiles using the control variable (book to market, capital gains overhang), and then within each quintile, we sort stocks into quintile portfolios based on the IVnews (IVnonews), so that L(H) contains stocks with the lowest (highest) IVOL, IVnews, and IVnonews. For brevity, we only report the average returns across the five control quintiles to produce quintile portfolios with dispersion in IVnews (IVnonews) but with similar levels of the control variable.

Particularly, the first two columns of Table 7 report returns averaged across five portfolios to produce quintiles with dispersion in IVnews in Panel A (IVnonews in Panel B), but with similar levels of capital gains overhang (CGO). The last two columns of Table 7 report returns averaged across five portfolios to produce quintiles with dispersion in IVnews in Panel A (IVnonews in Panel B), but with similar levels of book-to-market (BM). We report the zero-cost portfolios (H-L) and the alphas for portfolios (FF3 alpha) sorting on overvaluation in the first stage and news (non-news) volatility in the second stage in both equally weighted (value-weighted) portfolio returns. The Newey-West (1987) t-statistics in parentheses.

In this table, we present the double-sorted portfolio results based on the overvaluation variable and news idiosyncratic volatility (Non-news Idiosyncratic Volatility). We use the book-to-market ratio (BM) and CGO as measures of overvaluation (DeLisle et al., 2016). For each month, we first sort stocks into quintiles based on overvaluation measures. Within each overvaluation quintile, we sort stocks into quintiles based on news idiosyncratic volatility (Non-news Idiosyncratic Volatility). We finally form zero-cost portfolios that are long the highest volatility quintile and short the lowest volatility quintile. In Panel A (Panel B), we provide the results in equal weight and value weight of the stocks in the portfolios based on news idiosyncratic volatility (Non-news Idiosyncratic Volatility). Our sample is from June 2005 to June 2017. Robust Newey-West t-statistics (estimated with four lags) are given in parentheses. We denote statistical significance at the 1%, 5%, and 10% levels with \*\*\*, \*\*, and \*, respectively.

**Table 7. Returns on double-sorted: Overvaluation, news idiosyncratic volatility, and non-news idiosyncratic volatility**

	CGO				BM			
	EW		VW		EW		VW	
	Average return	FF3 Alpha	Average return	FF3 Alpha	Average return	FF3 Alpha	Average return	FF3 Alpha
<b>Panel A: Overvaluation and News Volatility</b>								
L	0.0167 (0.87)	-0.0050 (-1.02)	0.0049 (0.25)	-0.0023 (-0.49)	0.0468*** (3.11)	0.0172** (2.41)	0.0379*** (2.62)	0.0119* (1.66)
2	0.0375** (2.37)	0.0030 (1.34)	0.0254* (1.73)	0.0020 (0.70)	0.0341*** (2.67)	0.0048 (0.87)	0.0269** (2.20)	0.0002 (0.05)
3	0.0214* (1.74)	-0.0008 (-0.33)	0.0130 (1.11)	-0.0011 (-0.55)	0.0522*** (3.64)	0.0308*** (3.31)	0.0463*** (3.36)	0.0279*** (3.05)
4	0.0451*** (2.82)	0.0087*** (3.00)	0.0343** (2.41)	0.0062** (2.09)	0.0351*** (2.65)	0.0075 (1.48)	0.0305** (2.35)	0.0069 (1.33)
H	0.0447** (2.52)	0.0229** (2.20)	0.0350** (1.97)	0.0182* (1.69)	0.0346** (2.31)	0.0052 (0.82)	0.0293** (2.05)	0.0033 (0.51)
H_L	0.0280* (1.79)	0.0279* (1.94)	0.0301 (1.61)	0.0205* (1.87)	-0.0122 (-0.97)	-0.0120 (-1.08)	-0.0086 (-0.59)	-0.0086 (-0.74)
<b>Panel B: Overvaluation and Non-News Volatility</b>								
L	0.0349*** (3.04)	0.0084*** (3.26)	0.0253** (2.37)	0.0044* (1.71)	0.0311*** (2.70)	0.0040 (1.59)	0.0219** (2.09)	0.0019 (0.71)
2	0.0304*** (2.66)	0.0037* (1.82)	0.0214** (2.00)	0.0027 (1.22)	0.0293*** (2.61)	0.0023 (1.06)	0.0211* (1.99)	0.0015 (0.55)
3	0.0251** (2.21)	-0.0008 (-0.45)	0.0164 (1.50)	-0.0017 (-0.79)	0.0267** (2.32)	0.0008 (0.34)	0.0173 (1.62)	-0.0004 (-0.19)
4	0.0232** (2.05)	-0.0021 (-1.18)	0.0156 (1.45)	-0.0012 (-0.49)	0.0237** (2.05)	-0.0019 (-1.00)	0.0163 (1.46)	-0.0002 (-0.12)
H	0.0122 (1.11)	-0.0121*** (-5.62)	0.0077 (0.70)	-0.0099*** (-3.89)	0.0132 (1.18)	-0.0102*** (-4.23)	0.0109 (0.97)	-0.0069** (-2.35)
H_L	-0.0227*** (-7.76)	-0.0205*** (-7.03)	-0.0176*** (-4.66)	-0.0143*** (-4.19)	-0.0179*** (-5.95)	-0.0142 (-5.00)	-0.0110*** (-3.06)	-0.0088 (-2.64)

In Panel A, we cannot find stronger evidence to support the mispricing correction hypothesis in both equal and value weighted portfolios based on our measures of overvaluation. When using CGO, the portfolio return is fluctuant and the H-L portfolio return is positive and significant at 10% for EW, but insignificantly positive for VW portfolio return. Similarly, when we measure overvaluation with the book-to-market ratio, there is no pattern in their portfolios returns, and the zero-cost portfolio return is insignificantly negative.

In Panel B, we reject the notion that overvaluation is the sole source of the negative correlation between non-news volatility and returns. After controlling for the CGO, the relationship between IVnonews and future returns is still significantly and economically negative. For EW (FF3 alpha) portfolio return, the portfolio returns monotonically decrease in overvaluation, decreasing from 0.0349 (0.0084) for the lowest IVnonews to 0.0122 (−0.0121) for the highest IVnonews. This pattern is also found in VW portfolio returns.

Using book to market as our measure of overvaluation also generates similar results. The portfolio returns display a decreasing pattern in both EW and VW portfolio returns. We find that all the zero-cost portfolios earn significantly negative returns and alphas. The EW (VW) H-L portfolio return in −0.0179 (−0.0110) and significant at the 1% (1%) level, while the EW (VW) FF3 alpha portfolio returns is −0.142 (−0.0088) and significant at the 1% (1%) level. The results from Panel A and Panel B imply that the overvaluation is not the source of the pricing of non-news volatility. This result is in line with the findings of DeLisle et al. (2016) for non-news idiosyncratic volatility in the US market.

#### 4. Conclusion

This paper investigates the negative relationship between idiosyncratic volatility and future return in the Chinese stock market from July 2005 to June 2017. The present study is designed to determine the effect of firm-specific news on the idiosyncratic volatility and future return relationship by using portfolio analysis and Fama and MacBeth (1973) regressions to clarify this phenomenon. This study provides the evidence of the pricing of the negative relation between non-news volatility and future returns in the Chinese stock market. These results are robust after controlling for several important factors, such as market beta, size, book-to-market ratio, momentum, liquidity, and maximum return.

Furthermore, these results are robust after controlling for seasonality effect, overreaction, and alternative idiosyncratic volatility measure. However, after adjusting by additional macroeconomic variables, the Chinese four-factor model and the salience trading volume factor, the average returns on zero-investment IVOL and non-news IVOL portfolios turn to become insignificant, indicating that they may be one driver of the IVOL puzzle in the Chinese stock market. Thus, our study contributes to a better understanding of the role of conditional idiosyncratic volatility in asset pricing.

#### Acknowledgements

We thank the editor and anonymous referees for their comments and suggestions.

#### Funding

This research is funded by Funds for Science and Technology Development of the University of Danang under project number [B2020-DN04-37].

#### Author details

Van Hai Hoang<sup>1</sup>

E-mail: [hoangvanhaidhkt@gmail.com](mailto:hoangvanhaidhkt@gmail.com)

ORCID ID: <http://orcid.org/0000-0003-2645-3545>

<sup>1</sup> University of Economics, The University of Danang, Danang, Vietnam.

#### Disclosure statement

No potential conflict of interest was reported by the author(s).

#### Citation information

Cite this article as: Firm-specific news and idiosyncratic volatility anomalies: Evidence from the Chinese stock market, Van Hai Hoang, *Cogent Economics & Finance* (2022), 10: 2127489.

#### Note

1. The special treatment (ST) firms usually have the distressed financial situation. Shanghai and Shenzhen Stock Exchange designate firms “ST” that operate at a net loss for two consecutive years

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## Appendix A: Construction of Control Variables

**Market beta (BETA):** Market beta of each stock is also estimated following Fama and French (1993). Firstly, the estimates of betas are computed for all firms using observations of 60 months and requiring a minimum of 24-month observation. Then, based on each stock size and its beta, we form the equal-weighted returns of the 5-by-5 portfolios, and they will be rebalancing each month. The returns of these portfolios, constructed by sizes and betas, are regressed on both contemporary and one-month lagged market return together. The BETAs of the portfolios are measured as the sum of these two posterior coefficients. These ex-post portfolio BETAs are reassigned to each stock contained into size-beta portfolios to avoid an errors-in-variables problem. Thus, the firm-month  $t$  beta is the beta of the portfolio in which it is included in month  $t$ .

**Firm size (SIZE):** Following existing literature, firm size is measured by the natural logarithm of the market value of equity at the end of month  $t-1$ .

**Book-to-market ratio (BM):** Following Fama and French, (1992), the book-to-market is the ratio of book value of common equity at the end of fiscal year  $t-1$  to market value of equity at the end of December of year  $t-1$ .

**Momentum (MOM):** Following Jagadeesh and Titman (1993), the momentum in month  $t$  is calculated as the cumulative return from month  $t-12$  to month  $t-2$ .

**Illiquidity (ILLIQ):** Following Amihud (2002), the illiquidity for each stock in month  $t$  is measured as the ratio of the absolute monthly stock returns to its dollar trading volume:

**Short-term return reversal (REV):** Following Jegadeesh (1990) and Lehmann (1990), the return reversal is defined as the return of the stock over the previous month.

**Maximum return (MAX):** Following Bali et al. (2011), the maximum return is defined as the maximum daily return within a month.

**Capital gains overhang (CGO):** Following Bhootra and Hur (2015), the capital gains overhang for month  $t$  is the difference between the adjusted price at the end of month  $t-1$  and the contemporaneous reference price of the average investor divided by the adjusted price at the end of month  $t-1$ . The reference price is estimated by exponentially smoothing the daily split-adjusted price time-series using the daily turnover as the smoothing factor.

## Appendix B: IVnews (IVnonews) and macroeconomic variables

We estimate the risk-adjusted returns of the quintile portfolios sorted by IVnews (IVnonews) by Fama–French factors in addition to macroeconomic variables, including Industrial Added Value (IAV), Consumer Price Index (CPI), Producer Price Index (PPI), Macro-Economic Climate Index (MECI), and Manufacturing Purchasing Managers’ Index (MPMI). The risk-adjusted returns adjusted by additional macroeconomic variables, which are called “macro” are estimated as Equation (6).

$$(H - L)_t = \alpha + \beta_1 \text{MKT}_t + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \sum_1^5 \text{MAC}_{t-1} + \epsilon_t \quad (6)$$

H-L is defined as the monthly return on the portfolio that longs the top quintile (High IVnews, High IVnonews) and shorts the bottom quintile (Low IVnews, Low IVnonews). We report the results of regressions of monthly value- and equal-weighted IVnews (IVnonews) premium on market return in excess of risk-free rate (MKT), size factor (SMB), book-to-market factor (HML), and macroeconomic variables (MAC). Newey–West (1987) adjusted standard errors are used to compute t-statistics (in parentheses). Significance levels at 1%, 5%, and 10% are presented by asterisks of \*\*\*, \*\*, and \*, respectively.

	IVnews		IVnonews	
	EW	VW	VW	VW
MKT	0.0929 (0.7280)	0.0620 (0.5040)	0.1281*** (4.1914)	0.2150*** (5.0088)
SMB	−0.3220* (−1.8719)	−0.2509 (−1.5070)	−0.2776*** (−5.4454)	−0.2456* (−1.7876)
HML	−0.2889 (−1.3576)	0.0285 (0.1395)	−0.4399*** (−5.2643)	−0.3732* (−1.9085)
IAV	−0.1995 (−0.8361)	−0.2068 (−0.7192)	0.0355 (0.3364)	0.1023 (0.5812)
CPI	−0.7984 (−1.0799)	−0.8818 (−1.1423)	0.2386 (1.0611)	−0.3187 (−0.8800)
PPI	0.2850 (0.6430)	0.2486 (0.5357)	−0.0215 (−0.1991)	0.0698 (0.4544)
MECI	1.4601* (1.7518)	1.9571** (2.2608)	−0.0225 (−0.1043)	0.3142* (1.7436)
MPMI	−0.0507 (−0.0958)	−0.3075 (−0.5299)	−0.0380** (−2.0310)	−0.5149** (−2.2656)





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