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Idiosyncratic volatility and firm-specific news: evidence from the Chinese stock market

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ABSTRACT
This study investigates the effect of firm-specific news on the pricing of idiosyncratic volatility (IVOL) in China. Using a sample of non-financial A-share listed firms from January 2006 to June 2018, we find that the predictive ability of IVOL is much weaker around firm announcements compared to that without news, suggesting that the limited arbitrage cannot disentangle the IVOL puzzle completely in the emerging market. Additionally, we investigate the effect of news sentiment on the predictive ability of IVOL and find that it is much stronger following bad news compared to good news. Finally, when we include the macroeconomic variables known to predict returns to adjust the systematic risk, we obtain novel findings that the negative premium of IVOL becomes insignificant, suggesting that the negative premium is time-varying with macroeconomy.

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1. Introduction

The relation between idiosyncratic volatility (hereafter IVOL) and expected returns has attracted considerable attention from financial researchers. The classical asset pricing theories predict no relation (Sharpe, 1964; Black, 1972; Lintner, 1975) or a positive relation (Levy, 1978; Merton, 1987) between IVOL and expected returns. Previous literature investigates the time-series relation between IVOL and expected returns empirically at market level, and obtain mixed evidence (Campbell et al., 2001; Goyal & Santa-Clara 2003; Bali et al., 2005; Guo & Savickas, 2006; Fazil & İpek, 2013). Ang et al. (2006, 2009) investigate the relation in cross-section between IVOL and expected returns at stock level and further address a phenomenon that the stocks with higher IVOL underperform the lower ones significantly in the U.S. and 23 developed equity markets. Since this phenomenon conflicts with the basic rule of risk-

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return trade-off in financial economics and cannot be explained by existing theories, it is called 'IVOL puzzle' and has raised considerable concern from financial researchers. Some follow-up studies investigate the presence of the IVOL puzzle in emerging stock markets and obtain mixed evidence. For instance, various literature report consistent evidence for the IVOL puzzle in China (Nartea et al., 2013; Wan, 2018; Gu et al., 2018) and contrary evidence from Southeast Asian stock markets (Nartea et al., 2011).

The role of firm-specific news is critical in the pricing of IVOL given the effect of news on the changes of IVOL and on mispricing (DeLisle et al., 2016; Shi et al., 2016). Specifically, the number of news announcements has a significantly positive impact on the volatility of stock returns (Kalev et al., 2004; Bali et al., 2018). Consequently, firm-specific announcements are inclined to raise the IVOL level and further deter the arbitrage activities, and therefore the stock mispricing is more likely to occur. From the view of investor attention, firm-specific news is a useful proxy for investor attention (Barber & Odean, 2008). Compared to professional institutional investors, individual investors are not sophisticated to analyze the information and search which stock they should buy, so they are more susceptible by events that grab their attention, such as firms experiencing news announcements. In consequence, the excessive noise trading induced by news would deviate the stock price from the fundamental value, and hence mispricing occurs. Therefore, the firm announcements are important to explain the IVOL puzzle and could be incorporated to evaluate the limits to arbitrage and mispricing explanation (Gu et al., 2018; Zaremba & Szczygielski, 2019).

Despite the important role played by firm-specific news, the studies incorporating news to IVOL puzzle are relatively rare and almost focus on the U.S. market. To the best of our knowledge, there are no relevant studies in emerging markets. Therefore, this study aims to fill this gap by investigating the influence of firm announcements on the IVOL puzzle in China. We focus on the Chinese stock market for the following reasons. Firstly, after three decades of development, China's stock market has grown to over $7 trillion in market capitalization by May 2017, becoming the world's second-largest equity market (Carpenter & Whitelaw, 2017). Secondly, the Chinese stock market is dominated by individual investors, who are easily influenced by firm-specific news with limited ability to analyze arrival information. Thus, the Chinese stock market should suffer more severe mispricing, which provides us a better context to examine the mispricing explanation for IVOL puzzle. Thirdly, compared to U.S., there are various unique trading rules and regulations in the Chinese security market, which may cause greater market inefficiency. For example, short selling was prohibited until the China Securities Regulatory Commission (CRSC) introduced the margin trading pilot program in March 2010. Only stocks that meet certain criteria are available for margin trading. Moreover, the daily price limits system may cause higher volatility on subsequent days, delay price discovery process, and interfere with trading (Kim & Rhee, 1997). In short, the above characteristics make the Chinese stock market less efficient than the U.S., and this study could provide out-of-sample evidence. Thus, the primary purpose of our research is to investigate the news effect on the pricing of IVOL. The second purpose is to distinguish the effect of news sentiment on the predictive ability of IVOL. The third purpose is to investigate the role of macroeconomic variables played in disentangling the IVOL puzzle.

Using a sample of non-financial A-share firms listed on the Shanghai and Shenzhen Security Exchanges from January 2006 to June 2018, we first perform one-way portfolio analysis and firm-level decile Fama-MacBeth regressions to investigate the pricing of IVOL involved in firm announcements as well as the IVOL without news. We find that the predictive ability of IVOL is much weaker around firm announcements, which is conflicting with the limited arbitrage explanation for IVOL puzzle. Then we investigate the influence of news sentiment on the pricing of IVOL by one-way portfolio analysis. The results show that the negative premium of IVOL is greater following bad news compared to good news. Finally, we include the macro-economic factors known to predict returns to adjust systematic risk and obtain striking findings that the negative premium of the long-short IVOL portfolio becomes insignificant. Such result suggests that the negative premium of the IVOL portfolios is time-varying with macroeconomy, and the macroeconomic variables may contribute to disentangling the IVOL puzzle in the Chinese stock market. Our findings are robust to alternative IVOL measures adjusted by Fama-French five-factor model.

Our study contributes to the literature from three perspectives. Firstly, we provide out-of-sample evidence about the influence of firm-specific news on the pricing of IVOL from the largest emerging market. Our study involves all-type of firm-specific news and thus may shed new light on the strand of literature that explains the IVOL puzzle from the view of the information content of IVOL, which mainly focused on the specified firm-level events. Secondly, our study distinguishes the effect of the news sentiment on the predictive ability of IVOL. Finally, our study involves macro-economic factors into the IVOL puzzle in China and offers novel findings about the critical role played by macroeconomic factors.

The remainder of this article is organized as below. Section 2 describes our sample and variables construction in our study. Section 3 performs empirical tests by three steps. Firstly, we investigate the effect of firm-specific news on the pricing of IVOL by one-way portfolio analysis and firm-level decile Fama-MacBeth regressions. Next, we investigate the effect of news sentiment on the pricing of IVOL. Finally, we conduct some robust tests to the influence of macroeconomic factors and alternative IVOL measures. Section 4 concludes.

2. Sample and variable descriptions

2.1. Sample description

Our original sample contains all the Chinese A-share firms listed on the Shanghai and Shenzhen Security Exchanges with available stock returns and company financial statement data. We collect the firm-specific news data from the Event Research Database included in the CSMAR database. Specifically, the firm-specific news is defined as a public declaration or announcement of 1) a CEO change, 2) an equity structure change, 3) External guarantee, 4) IPO, 5) Lawsuit, 6) an M&A, 7) Private placement, 8) Profit sharing- or dividends payout, 9) Public Offering, 10) Right issue, 11) Statement Release Date, 12) Violation, and 13) Others.

The firm-level event data is available from the year 2005, but the data is very few. Therefore, our sample spans from January 2006 to June 2018, covering 2579 unique firms. The stock trading data, financial statement data, and Fama and French (2015) five factors are collected from the CSMAR database. The Fama and French (1993) three factors and risk-free rate data are collected from the RESSET database.

Furthermore, we clean the data as below. Firstly, we eliminated financial firms in the financial sectors and firms with negative book equity (Fama & French, 1992). Next, we delete firms with less than 250 trading days throughout the sample period. Given the unique characteristics of the Chinese stock market, we delete the trading days under special treatment and IPO days that are not subject to daily price limits. Finally, we exclude the firm-month observations with less than 15 trading days within one month. After applying the above filters, the number of stocks in the final sample ranges from 1380 in 2006 to 2510 in 2018.

Finally, following Yi and Mao (2009), we select the following macroeconomic variables for the Chinese market: 1) Inflation rate, measured as the monthly year-on-year Consumer Price Index (CPI) growth; 2) Industrial Added Value (IAV) year-on-year growth; 3) Manufacturing Purchasing Managers' Index (PMI) year-on-year growth; 4) Producer Price Index (PPI) year-on-year growth; and 5) Macro-Economic Climate Index (ECI) year-on-year growth. The data is collected from the CEInet Statistics database.

2.2. Variables construction

For the independent variables, the idiosyncratic volatility (IVOL) adopted in this study is estimated following Ang et al. (2006) and then modified following DeLisle et al. (2016). Precisely speaking, we first estimate the standard IVOL as the standard deviation of daily residuals adjusted by the Fama and French (1993) three-factor model over previous month. In each month for each stock, we run the following regression to calculate the daily residuals ($\varepsilon_{i,d}$):

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_1 MKT_d + \beta_2 SMB_d + \beta_3 \; HML_d + \varepsilon_{i,d} \tag{1}$$

where $R_{i,d}$ is the daily return of stock i on day d, $R_{f,d}$ is the daily risk-free rate on day d, and MKT_d, SMB_d, and HML_d are the daily Fama and French (1993) three factors.

Then we modify the conventional IVOL by multiplying square root of 30 in order to transform the daily measure of IVOL to a monthly estimate (i.e., 30 days) as in Eq. (2).

$$IVOL_{i,t} = \sqrt{\frac{30}{D_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} \varepsilon_{i,d}^2} \tag{2}$$

where $D_{i,t}$ is the number of trading days for stock i in month t, and $\varepsilon_{i,d}^2$ is the square of the daily residuals estimated from Eq. (1). At least 15 trading days in one month is required to calculate the monthly IVOL.

In order to incorporate the firm-specific news into the IVOL puzzle, we decompose the IVOL into news and non-news measures by adjusting Eq. (2) as below:

$$IVnews_{i,t} = \sqrt{\frac{30}{N_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} \left(\eta_{i,d} \times \varepsilon_{i,d}^2\right)} \tag{3a}$$

$$IVnonews_{i,t} = \sqrt{\frac{30}{D_{i,t} - N_{i,t}}} \times \sqrt{\sum_{d=1}^{D_{i,t}} \left((1 - \eta_{i,d}) \times \varepsilon_{i,d}^2\right)} \tag{3b}$$

where $N_{i,t}$ is the number of trading days over month t in which a firm makes an announcement, $\eta_{i,d}$ is a dummy variable which takes the value of one if a firm releases an announcement on day d and zero, otherwise. We apply an event window of four days around the release date. Specifically, if a firm makes an announcement on day d, then the days from $d-1$ to $d+2$ over month t are determined as event days. Thus, $N_{i,t}$ is a multiple of four typically except for the case where a news announcement is made on the first or last day or the day before the last day of a calendar month.

The control variables employed in the cross-sectional regressions include a set of firm characteristics, including market beta (BETA), firm size (SIZE), book-to-market ratio (lnBM), short-term momentum (MOM), illiquidity (ILLIQ), short-term return reversal (STREV), and maximum daily return (MAX). These firm characteristics have been documented excessively as return predictors in the cross-section in China (Chen et al., 2010; Cakici et al., 2017; Carpenter et al., 2021). Specifically, BETA is estimated from regressing daily firm excess returns on daily current, lead, and lagged market excess returns over previous month following Scholes and Williams (1977) and Dimson (1979) as in Eqs. (4) and (5).

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \varepsilon_{i,d} \tag{4}$$

$$\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i} \tag{5}$$

where $R_{i,d}$ is the daily return of stock i on day d, $R_{f,d}$ is the daily risk-free rate on day d, and $R_{m,d}$ is the daily market return on day d. SIZE is estimated as the natural logarithm of the floated market capitalization at the end of last month. lnBM is calculated as the natural logarithm of the book-to-market ratio at the end of December last year. MOM is estimated as the cumulative return from month $t-7$ to $t-2$, as in Jegadeesh and Titman (1993). ILLIQ is estimated as the ratio of the absolute monthly stock returns to its trading volume in RMB over month $t-1$ and then scaled by 10^6 following Amihud (2002). STREV is measured as one-month lagged return for each stock, as in Jegadeesh (1990). MAX is measured as the maximum daily return in month $t-1$, as in Bali et al. (2011).

Table 1 displays the number of firms by year (Panel A) and the descriptive statistics of above variables (Panel B and C). The descriptive statistics are estimated using two-step procedures. The cross-sectional statistics of each variable in each month are calculated firstly and then these statistics are averaged in time-series.

Table 1. Summary statistics.

Panel A: Number of firms by year

Year	2006	2007	2008	2009	2010	2011	2012
N. of Firms	1,380	1,480	1,553	1,612	1,832	1,978	2,054
Year	2013	2014	2015	2016	2017	2018	Total
N. of Firms	2,053	2,122	2,252	2,386	2,526	2,510	2,579

Panel B: Descriptive statistics

Variable	Mean	Std. Dev	Median	P25	P75	Skew
RET	0.0207	0.1046	0.0058	−0.0441	0.0690	1.3998
IVOL	0.1033	0.0488	0.0949	0.0715	0.1256	3.3976
IVnews	0.1518	0.1326	0.1147	0.0691	0.2108	2.9847
IVnonews	0.1003	0.0465	0.0919	0.0688	0.1224	2.3886
BETA	1.1536	0.8201	1.1442	0.6927	1.6084	0.0635
SIZE	21.9438	0.9563	21.8121	21.2802	22.4745	0.8463
lnBM	−1.0223	0.6187	−0.9819	−1.3712	−0.6235	−0.8624
STREV	0.0215	0.1068	0.0064	−0.0437	0.0695	1.5446
MOM	0.1501	0.2854	0.0957	−0.0328	0.2683	1.9179
MAX	0.0585	0.0242	0.0543	0.0407	0.0738	1.1270
ILLIQ	0.1578	0.2262	0.0994	0.0404	0.2081	3.2436

Panel C: Correlations

	RET	*IVOL*	*IVnews*	*IVnonews*	*BETA*	*SIZE*	*lnBM*	*STREV*	*MOM*	*MAX*	*ILLIQ*
RET		**−0.068**	−0.02	**−0.06**	**0.04**	**−0.05**	0.03	**−0.06**	−0.01	**−0.05**	**0.05**
IVOL	**−0.10**		**0.77**	**0.92**	**0.07**	**−0.06**	**−0.15**	**0.42**	**0.25**	**0.74**	−0.02
IVnews	**−0.05**	**0.72**		**0.51**	**0.07**	**−0.10**	**−0.17**	**0.45**	**0.17**	**0.54**	0.02
IVnonews	**−0.10**	**0.94**	**0.49**		**0.07**	**−0.08**	**−0.14**	**0.39**	**0.23**	**0.68**	−0.02
BETA	**0.04**	**0.08**	**0.08**	**0.08**		**−0.04**	−0.01	**−0.08**	**0.04**	**0.17**	**−0.05**
SIZE	**−0.06**	**−0.04**	**−0.08**	**−0.06**	**−0.04**		**0.11**	**0.05**	**0.13**	**−0.03**	**−0.43**
lnBM	0.02	**−0.17**	**−0.18**	**−0.17**	**−0.02**	**0.11**		0.01	**0.04**	**−0.07**	**−0.07**
STREV	**−0.07**	**0.35**	**0.41**	**0.33**	**−0.10**	**0.04**	0.02		**−0.04**	**0.46**	**0.09**
MOM	−0.02	**0.23**	**0.17**	**0.21**	**0.03**	**0.11**	**0.06**	**−0.06**		**0.13**	**−0.10**
MAX	**−0.07**	**0.74**	**0.50**	**0.68**	**0.19**	−0.02	**−0.09**	**0.45**	**0.12**		**−0.03**
ILLIQ	**0.06**	**−0.04**	0.01	−0.03	**−0.04**	**−0.52**	**−0.03**	0.05	**−0.11**	**−0.05**	

Note: This table shows the number of firms by year (Panel A) and summary statistics of variables (Panel B). The sample period spans from January 2006 to June 2018. The summary statistics are estimated using two-step procedures. The cross-sectional statistics of each variable in each month are firstly calculated and then these statistics are averaged in time-series. The Pearson (above diagonal) and Spearman (below diagonal) correlations are displayed in Panel C. The correlations which are significant at 5% level are expressed in bold font.
Source: The Authors.

Panel B shows that the monthly returns are positively skewed. The mean monthly return is 2.07%, while the median is 0.58%, with the skewness of approximately 1.40. The mean of the IVOL, news IVOL, and non-news IVOL are 0.1033, 0.1518, and 0.1003, respectively. The mean and standard deviation of IVOL around news announcement are the highest, while that of IVOL without news are the lowest. This pattern is consistent with our expectation that the news announcements fluctuate the stock prices and increase the return volatility.

Panel C displays the time-series average of the correlations in cross section among variables. The Pearson (Spearman) correlations are displayed in the above (below) diagonal of the correlation matrix. It is shown that the monthly returns are correlated negatively with the one-month lagged IVOL, with a Pearson correlation of −0.07, which is statistically significant at 5% level. In addition, the IVOL is highly correlated with MAX, with a correlation of over 70%, consistent with the existing evidence. Besides, IVOL is positively correlated with STREV, with a high Pearson (Spearman) correlation of 42% (35%).

3. Empirical results and discussions

3.1. News effect on the pricing of IVOL

In this section, we investigate the news effect on the pricing of IVOL by one-way portfolio analysis and firm-level decile Fama-MacBeth regressions.

3.1.1. One-way portfolio sorting on IVOL

In this subsection, we first test whether the IVOL puzzle exists in our sample. Then we investigate the predictive ability of news and non-news IVOL by one-way portfolio sorting approach.

In details, at the start of each month, all the stocks are ranked into quintile portfolios according to IVOL, news IVOL and non-news IVOL. Then the average return of each quintile portfolios over the subsequent month is calculated both equal- and value-weighted. The zero-investment portfolio is also constructed by longing the highest quintile and short selling the lowest quintile. Finally, the time-series average of the raw returns and FF-3 alphas are calculated. The Newey and West (1987) t-statistics adjusted by four lags are also estimated to justify the significance of the portfolio returns. The results are reported in Table 2.

Panel A shows that the average returns of the zero-investment portfolios are negative and statistically significant for both equal- and value-weighted portfolios,

Table 2. Raw returns and FF-3 alphas on quintiles sorted by IVOL, IVnews, and IVnonews.

		L	2	3	4	H	H-L
Panel A: Idiosyncratic Volatility - IVOL							
EW	Raw return	0.0278***	0.0260**	0.0230**	0.0178*	0.0087	−0.0191***
		(2.73)	(2.61)	(2.26)	(1.77)	(0.89)	(−8.25)
	FF-3 alpha	0.0065***	0.0048**	0.0019	−0.003	−0.0119***	−0.0184***
		(2.68)	(2.33)	(0.90)	(−1.46)	(−5.51)	(−7.56)
VW	Raw return	0.0171*	0.0186**	0.0185*	0.0128	0.0079	−0.0092**
		(1.85)	(2.04)	(1.87)	(1.27)	(0.80)	(−2.51)
	FF-3 alpha	0.0029	0.0029	0.0032	−0.0024	−0.0086***	−0.0115***
		(1.16)	(1.27)	(1.31)	(−0.94)	(−2.99)	(−3.19)
Panel B: News Idiosyncratic Volatility - IVnews							
EW	Raw return	0.0182	0.0120	0.0192*	0.0166	0.0070	−0.0112
		(1.60)	(1.28)	(1.78)	(1.64)	(0.82)	(−1.66)
	FF − 3 alpha	−0.0009	−0.0103*	−0.0008	0.0008	−0.0132**	−0.0123
		(−0.17)	(−1.83)	(−0.18)	(0.20)	(−2.52)	(−1.60)
VW	Raw return	0.0071	0.0103	0.0145	0.0139	0.0042	−0.0027
		(0.65)	(1.16)	(1.25)	(1.31)	(0.44)	(-0.38)
	FF-3 alpha	−0.0070	−0.0093*	−0.0046	−0.0042	−0.0133**	−0.0068
		(−1.13)	(−1.72)	(−0.97)	(−0.82)	(-2.47)	(-0.79)
Panel C: Non-News Idiosyncratic Volatility - IVnonews							
EW	Raw return	0.0268***	0.0254***	0.0235**	0.0185*	0.0088	−0.0180***
		(2.79)	(2.66)	(2.41)	(1.92)	(0.94)	(-8.93)
	FF-3 alpha	0.0062***	0.0046**	0.0027	−0.0019	−0.0114***	−0.0176***
		(2.79)	(2.24)	(1.34)	(−0.96)	(−5.53)	(−8.33)
VW	Raw return	0.0166*	0.0188**	0.0188*	0.0139	0.0076	−0.0090***
		(1.90)	(2.13)	(1.97)	(1.43)	(0.81)	(−2.66)
	FF-3 alpha	0.0023	0.0032	0.0034	−0.0013	−0.0088***	−0.0111***
		(1.00)	(1.53)	(1.58)	(−0.51)	(−3.28)	(−3.33)

Note: This table displays the time-series average of raw returns and FF-3 alphas on quintile portfolios ranked by IVOL (Panel A), IVnews (Panel B), and IVnonews (Panel C), respectively. The sample period spans from January 2006 to June 2018. Newey-West t-statistics with 4 lags are presented in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.
Source: The Authors.

consistent with the existing evidence (Nartea et al., 2013; Wan, 2018; Gu et al., 2018). Specifically, for the equal-weighted portfolios, the average raw returns and FF-3 alphas are both monotonically decreasing with IVOL. The investment strategy by longing the quintile H and short selling the quintile L yields a risk-adjusted return of −1.84% per month on average, which is economically and statistically significant. For the value-weighted portfolios, though the magnitude of the risk-adjusted return decreases to −1.15% per month, only 60% of equally weighted portfolios, it is still significantly negative at 1% level.

Panel B reports the average raw returns and FF-3 alphas for portfolios sorted by news IVOL (IVnews). There are no apparent patterns for the raw returns and FF-3 alphas from low to high IVnews portfolios both on equal- and value-weighted basis. For the H-L portfolio, the average raw returns and FF-3 alphas are negative but not statistically significant, indicating that the news IVOL is not priced in the cross-section, consistent with the results in DeLisle et al. (2016) for U.S. market.

Panel C reports the average raw returns and FF-3 alphas for portfolios sorted by non-news IVOL (IVnonews). The results are similar with that of IVOL portfolios, no matter for the pattern and magnitude. Specifically, the average raw return and FF-3 alphas of H-L portfolios on both equal- and value-weighted basis are negative and statistically significant at 1% level.

Above all, our findings show that the negative price of non-news IVOL is much stronger than the IVOL around firm-specific news. Based on the limits to arbitrage explanation, the news IVOL should be more negatively priced than non-news IVOL, since firm-specific news fluctuates the volatility of stock price, and hence causes more mispricing. Our findings suggest that the limited arbitrage cannot disentangle the negative premium of IVOL in the emerging market.

3.1.2. Firm-level decile Fama-MacBeth regressions

The portfolio sorting approach mentioned above is non-parametric and enables us to evaluate the relation between IVOL and expected stock returns without specifying a specific functional form. However, such analysis loses much information through aggregation, and it cannot control for multiple effects or factors simultaneously (Fama & French, 2008). Consequently, we conduct the firm-level Fama-MacBeth regressions as further robustness tests. By doing so, the pricing of news and non-news IVOL can be re-examined at the firm-level, and control for other well-known return predictors, including market beta (BETA), firm size (SIZE), book-to-market ratio (BM), short-term return reversal (STREV), short-term momentum (MOM), illiquidity (ILLIQ), and maximum daily return (MAX).

Instead of using basic values of explanatory variables, we follow the procedure in Mashruwala et al. (2006) to scale them into decile ranks ranging from −0.5 to 0.5. This approach can avoid the outlier problem in explanatory variables and make the regression coefficients comparable across firm characteristic variables. By this means, the regression coefficient on each explanatory variable, such as IVOL, can be explained as the return difference between the highest IVOL decile and the lowest one.

The process to scale the ranked variables are based on Eq. (6):

$$IndVar^{R}_{i,t} = \left[\frac{IndVar\_decile_{i,t} - 1}{9}\right] - 0.5 \tag{6}$$

where $IndVar\_decile_{i,t}$ is the decile rank of independent variable i over month t. The monthly scaled ranked variables are expressed with superscript 'R' in the regressions.

The firm-level Fama-MacBeth regressions are performed as shown below. In the first step, the monthly excess returns of each stock in each month are regressed on the lagged IVOL measures according to the baseline model as in Eq. (7):

$$R_{i,t+1} - R_{f,t+1} = \alpha_{0,t} + \beta_{1,t} IVOL^{R}_{i,t} + \beta_{2,t} IVnews^{R}_{i,t} + \beta_{3,t} IVnonews^{R}_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

where $R_{i,t+1}$ is the monthly return of stock i over month $t+1$, $R_{f,t+1}$ is the monthly riskfree rate over month $t+1$, $IVOL^{R}_{i,t}$, $IVnews^{R}_{i,t}$, and $IVnonews^{R}_{i,t}$ are the scaled ranked IVOL measures over month t. In this step, we obtain the monthly regression coefficients on IVOL measures. Next, the time-series averages of these regression coefficients are computed. The associated Newey-West t-statistics with four lags are also estimated to verify the significance of the average coefficients.

Next, in order to verify whether the IVOL effect obtained from the baseline model still exists after controlling for other return predictors, we repeat the same procedures based on Eq. (8):

$$R_{i,t+1} - R_{f,t+1} = \alpha_{0,t} + \beta_{1,t} IVOL^{R}_{i,t} + \beta_{2,t} IVnews^{R}_{i,t} + \beta_{3,t} IVnonews^{R}_{i,t} + \beta_{4,n,t} \sum_{n=1}^{N} X^{R}_{n,i,t} + \varepsilon_{i,t+1} \tag{8}$$

where $X^{R}_{n,i,t}$ is the set of control variables of stock i over month t, including BETA, SIZE, InBM, MOM, ILLIQ, STREV, and MAX.

Table 3 presents the time series average of the slopes on explanatory variables and Newey-West t-statistics. In general, the results in Table 3 are consistent with that in Table 2. For instance, in Model 1, the average coefficient on IVOL is −0.021 (t-statistics = −8.58), suggesting that the investment strategy that is longing highest IVOL decile and short selling lowest IVOL decile could produce monthly premium of −2.1% in the Chinese stock market. Both the magnitude and statistical significance are similar with that in the portfolio-level analysis. In Model 2, the average coefficient on IVOL is slightly different from that in Model 1, suggesting that the predictive ability of IVOL is robust to control for the well-known return predictors simultaneously. In addition, the average coefficient on MAX is −0.001 with a t-value of −0.35, suggesting that the IVOL effect could subsume the MAX effect in the Chinese market. Our results support the existing evidence based on Chinese dataset, such as Wan (2018) and Gu et al. (2018).

For news IVOL, the average slopes in univariate (Model 3) and multivariate (Model 4) models are −0.005 and 0.000, respectively, which are both slightly different from zero. Such findings indicate that the IVOL around firm-specific news announcements is not priced in the cross section in the Chinese stock market. For the non-news IVOL,

Table 3. Results from firm-level decile Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
IVOL^R	**−0.021*****	**−0.020*****				
	(−8.58)	(−9.42)				
IVnews^R			−0.005	0.000		
			(−0.35)	(0.01)		
IVnonews^R					**−0.020*****	**−0.016*****
					(−8.23)	(−9.26)
BETA^R		**0.013*****		−0.026		**0.014*****
		(5.78)		(−0.79)		(6.03)
SIZE^R		−0.007		0.026		−0.007
		(−1.51)		(0.66)		(−1.55)
LnBM^R		0.003		−0.005		0.002
		(0.81)		(−0.16)		(0.70)
MOM^R		**0.005***		−0.028		0.004
		(1.72)		(−1.12)		(1.60)
STREV^R		**−0.012*****		**−0.028****		**−0.013*****
		(−2.86)		(−1.99)		(−3.03)
ILLIQ^R		**0.014*****		0.025		**0.013*****
		(4.29)		(1.65)		(4.29)
MAX^R		−0.001		−0.006		**−0.004****
		(−0.35)		(−0.50)		(−2.10)

Note: This table displays the time-series average of slopes from the decile firm-level Fama-MacBeth regressions. The sample period spans from January 2006 to June 2018. Newey–West t-statistics with four lags are shown in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.
Source: The Authors.

the average slope on IVnonews in Model 5 is −0.020 (t-statistics = −8.23), which is negative and statistically significant at 1% level. After controlling for the firm characteristics in Model 6, the average slope slightly decreases to −0.016 (t-statistics = −9.26), but still highly significant at 1% level. These results indicate that the predictive ability of non-news IVOL is stronger than news IVOL, and it cannot be eliminated away by well-known predictors.

3.2. The effect of news sentiment on the pricing of IVOL

The prospect theory notes that people are more sensitive to losses than to gains (Kahneman & Tversky, 1979), so investors tend to overreact to bad news relative to good news. Thus, we argue that bad news causes greater fluctuation in stock prices relative to good news. In this subsection, we distinguish the effects of good and bad news on the pricing of IVOL. Unfortunately, there is no database that classifies firm-specific news by its sentiment in China, so we apply a simple method to classify news as good or bad news. Specifically, we define news as 'good news' if the subsequent holding period return following this news is not negative, and 'bad news', otherwise. The holding period following the news is set to seven market trading days. Since there are cases in which one firm makes more than one announcement within one month, we classify all firm-month observations into three types. Type 1 contains the observations with only good news, type 2 contains the observations with only bad news, while type 3 contains observations with both good and bad news within one month.

We then perform one-way portfolio sorting analysis to investigate the predictive ability of IVOL following good or bad news using the three types of samples above.

Table 4. Raw returns and FF-3 alphas on quintiles sorted by IVOL for good/bad news.

		L	2	3	4	H	H-L
Panel A: Good news							
EW	Raw return	0.0245***	0.0251***	0.0239***	0.0185**	0.0121	−0.0124***
		(3.10)	(3.14)	(3.15)	(2.19)	(1.42)	(−4.77)
	FF-3 alpha	0.0129***	0.0126***	0.0131***	0.0076***	0.0002	−0.0126***
		(9.22)	(6.13)	(5.36)	(3.35)	(0.10)	(−5.36)
VW	Raw return	0.0198***	0.0229***	0.0198***	0.0143*	0.0129	−0.0069
		(2.78)	(3.14)	(2.64)	(1.71)	(1.59)	(−1.43)
	FF-3 alpha	0.0151***	0.0162***	0.0154***	0.0103***	0.0060	−0.0091*
		(5.36)	(5.13)	(3.84)	(3.26)	(1.64)	(−1.72)
Panel B: Bad news							
EW	Raw return	0.0116	0.0101	0.0046	0.0024	−0.0108	−0.0224***
		(1.34)	(1.14)	(0.56)	(0.26)	(−1.24)	(−7.74)
	FF-3 alpha	−0.0015	−0.0040*	−0.0082***	−0.0101***	−0.0230***	−0.0216***
		(−0.66)	(−1.85)	(−4.52)	(−4.03)	(−12.39)	(−7.37)
VW	Raw return	0.0075	0.0000	−0.0004	−0.0014	−0.0151*	−0.0225***
		(0.83)	(0.00)	(−0.05)	(−0.16)	(−1.74)	(−4.11)
	FF-3 alpha	0.0002	−0.0085***	−0.0085***	−0.0104***	−0.0240***	−0.0242***
		(0.05)	(−3.25)	(−3.04)	(−3.19)	(−7.67)	(−5.15)
Panel C: Good & Bad news							
EW	Raw return	0.0161*	0.0165**	0.013	0.0078	−0.0005	−0.0166***
		(1.98)	(2.08)	(1.66)	(1.03)	(−0.06)	(−5.44)
	FF-3 alpha	0.0048**	0.0051***	0.0024**	−0.0023	−0.0108***	−0.0156***
		(2.52)	(2.93)	(2.01)	(−1.19)	(−5.87)	(−6.16)
VW	Raw return	0.0043	0.0097	0.0090	0.0030	−0.0014	−0.0057
		(0.62)	(1.28)	(1.23)	(0.38)	(−0.15)	(−1.23)
	FF-3 alpha	−0.0002	0.0042	0.0047**	−0.002	−0.0058**	−0.0056
		(−0.08)	(1.32)	(2.52)	(−0.79)	(−2.11)	(−1.52)

Note: This table reports raw returns and FF-3 alphas on portfolios ranked by IVOL for good news sample (Panel A), bad news sample (Panel B), and good & bad news sample (Panel C). The sample period is from January 2006 to June 2018. Newey–West t-statistics with four lags are shown in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.
Source: The Authors.

The results are shown in Table 4. Panels A, B, and C report the results for good news, bad news, and both good and bad news, respectively.

The results show that the negative price of IVOL is strongest following bad news, which is consistent with our expectations. In detail, for the firm-month observations with only good news and with confounding news, the relationship between IVOL and expected returns is significantly negative at 1% level for equal-weighted portfolios, while for value-weighted portfolios, it is not significant at 5% level. However, for the bad news sample, the average raw returns and risk-adjusted returns on the long-short portfolios are significantly negative at 1% level for both equal- and value-weighted portfolios. Such findings imply that bad news causes greater fluctuation in stock prices compared to good news, resulting in a greater negative price of IVOL. This finding is consistent with Ma et al. (2021), who mention that the Chinese security market reacts differently to positive and negative news, and this difference can be explained by the investors' attention bias.

3.3. Additional tests

In this section, we conduct additional tests to examine whether our results are robust to the macroeconomic factors and to the alternative IVOL measures estimated by the Fama and French (2015) five-factor model.

3.3.1. The influence of macroeconomic variables on the pricing of IVOL

Previous literature argues that stock volatility is strongly related to the macroeconomy (Binder & Merges, 2001; Flannery & Protopapadakis, 2002; Bali & Zhou, 2016). Traditional asset pricing models assume that idiosyncratic risk is firm-specific risk and is not critical to the valuation of stocks. However, Guo and Savickas (2006) find that IVOL is highly related to the consumption-wealth ratio and appears to be a pervasive macroeconomic variable. Subsequently, Guo and Savickas (2010) demonstrate that the IVOL factor constructed as the return difference between low and high stocks is a significantly priced factor in the cross section, and thus, they proposed that IVOL is a proxy for systematic risk. Recently, Aslanidis et al. (2019) constructed macro-finance factors from a larger pool of macroeconomic and financial variables to explain the IVOL puzzle.

Motivated by the above findings, we examine the role of macroeconomic variables in the explanation of the IVOL puzzle in China. Cheon and Lee (2018) investigate the time variation of the negative premium of MAX hedge portfolios in the Korean stock market. Following their procedures, we calculate the risk-adjusted returns of the IVOL quintile portfolios by FF-3 factors in addition to macroeconomic factors that are well known to explain stock returns in the Chinese security market. Such risk-adjusted returns are denoted by 'macro alpha', which are estimated as in Eq. (9).

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \sum_{i=1}^{5} Macrovars_{i,t-1} + \varepsilon_{p,t} \tag{9}$$

where $R_{p,t}$ is the monthly return of portfolio p over month t, $R_{f,t}$ is the risk-free rate over month t, MKT_t, SMB_t, and HML_t are the monthly Fama and French factors (1993) in month t, and $Macrovars_{i,t-1}$ are macroeconomic variables widely used to control for macroeconomic effects in the Chinese market.

Table 5. Macro alphas on quintile portfolios sorted by IVOL and IVnonews.

		L	2	3	4	H	H-L
Panel A: Idiosyncratic Volatility - IVOL							
EW	FF-3 alpha	0.0069***	0.0052**	0.0024	−0.0024	−0.0118***	−0.0187***
		(2.97)	(2.56)	(1.19)	(−1.21)	(−5.63)	(−8.31)
	Macro alpha	−0.0824	−0.1046	−0.0183	−0.1171	−0.0223	0.0601
		(−0.50)	(−1.04)	(−0.15)	(−1.19)	(−0.14)	(0.46)
VW	FF-3 alpha	0.0025	0.0033	0.0035	−0.0021	−0.0088***	−0.0112***
		(1.06)	(1.52)	(1.57)	(−0.84)	(−3.13)	(−3.17)
	Macro alpha	−0.1348	−0.0953	−0.0911	−0.1640	−0.0326	0.1022
		(−0.84)	(−0.64)	(−0.65)	(−1.27)	(−0.19)	(0.51)
Panel B: Non-News Idiosyncratic Volatility - IVnonews							
EW	FF-3 alpha	0.0062***	0.0046**	0.0027	−0.0019	−0.0114***	−0.0176***
		(2.79)	(2.24)	(1.34)	(−0.96)	(−5.53)	(−8.33)
	Macro alpha	−0.0904	−0.1125	−0.0220	−0.1319	0.0148	0.1052
		(−0.55)	(−1.03)	(−0.19)	(−1.34)	(0.10)	(0.81)
VW	FF-3 alpha	0.0023	0.0032	0.0034	−0.0013	−0.0088***	−0.0111***
		(1.00)	(1.53)	(1.58)	(−0.51)	(−3.28)	(−3.33)
	Macro alpha	−0.1337	−0.1298	0.0241	−0.1763	−0.0199	0.1138
		(−0.81)	(−1.06)	(0.19)	(−1.27)	(−0.12)	(0.61)

Note: This table reports the FF-3 alphas and macro alphas for quintile portfolios ranked by IVOL. The sample period is from January 2006 to June 2018. The 'Macro alpha' is the risk adjusted returns adjusted by FF-3 factors and additional macroeconomic variables. Panel A and Panel B report the results for portfolios ranked by IVOL and IVnonews, respectively. Newey–West t-statistics with four lags are shown in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.
Source: The Authors.

Table 5 presents the macro alphas on the quintile portfolios ranked by IVOL (Panel A) and non-news IVOL (Panel B). For comparison, we also report the corresponding FF-3 alphas.

The results in Table 5 are striking. After adjusting the FF-3 alphas by additional macroeconomic factors, the macro alphas of zero-investment IVOL portfolios become statistically insignificant. These findings indicate that the negative premium of IVOL portfolios is time-varying with the macroeconomy in China. Herskovic et al. (2016) demonstrate that there is a common component in IVOL. Our results show that the common component is related to the macroeconomy, supporting the findings obtained from Aslanidis et al. (2019) in the developed market.

Table 6. Returns and FF-5 alphas on quintiles sorted by alternative IVOL measure.

		L	2	3	4	H	H-L
Panel A: Idiosyncratic Volatility - IVOL							
EW	Raw return	0.0272***	0.0261***	0.0229**	0.0175*	0.0092	−0.0180***
		(2.86)	(2.68)	(2.39)	(1.82)	(0.96)	(−8.99)
	FF-5 alpha	0.0045**	0.0015	−0.0016	−0.0068***	−0.0152***	−0.0197***
		(2.52)	(0.85)	(−1.11)	(−4.00)	(−9.84)	(−10.40)
	Macro alpha	−0.0530	−0.0478	−0.1098	−0.0802	−0.0579	−0.0050
		(−0.43)	(−0.44)	(−1.16)	(−0.79)	(−0.41)	(−0.04)
VW	Raw return	0.0154*	0.0203**	0.0164*	0.0138	0.0088	−0.0066*
		(1.84)	(2.19)	(1.79)	(1.40)	(0.92)	(-1.93)
	FF-5 alpha	−0.0001	0.0015	−0.0026	−0.0051**	−0.0104***	−0.0104***
		(−0.03)	(0.85)	(−1.44)	(−2.43)	(−4.82)	(−3.44)
	Macro alpha	−0.0445	−0.0333	−0.0397	−0.0785	−0.0544	−0.0099
		(−0.33)	(−0.23)	(−0.42)	(−0.61)	(−0.32)	(−0.05)
Panel B: News Idiosyncratic Volatility - IVnews							
EW	Raw return	0.0132	0.0163*	0.0259**	0.0144	0.0045	−0.0087
		(1.28)	(1.80)	(2.19)	(1.45)	(0.46)	(−1.60)
	FF-5 alpha	−0.0045	−0.0055	0.0024	−0.0043	−0.0201***	−0.0156***
		(−0.87)	(−1.22)	(0.34)	(−1.12)	(−5.93)	(−3.26)
	Macro alpha	0.2911	−0.3072	−0.1287	0.0051	0.0317	−0.2593
		(0.70)	(−1.28)	(−0.48)	(0.02)	(0.18)	(−0.59)
VW	Raw return	0.0019	0.0113	0.0246**	0.0128	0.0010	−0.0009
		(0.21)	(1.23)	(2.12)	(0.97)	(0.09)	(−0.16)
	FF-5 alpha	−0.0100*	−0.0095*	0.0021	−0.0034	−0.0187***	−0.0090*
		(−1.85)	(−1.88)	(0.33)	(−0.52)	(−4.78)	(−1.78)
	Macro alpha	0.3098	−0.5275	−0.2396	0.4195*	−0.1203	−0.4524
		(0.86)	(−1.49)	(−0.73)	(1.84)	(−0.61)	(−1.01)
Panel C: Non-News Idiosyncratic Volatility - IVnonews							
EW	Raw return	0.0266***	0.0260***	0.0229**	0.0182*	0.0094	−0.0172***
		(2.78)	(2.67)	(2.40)	(1.88)	(0.99)	(−8.95)
	FF-5 alpha	0.0039**	0.0015	−0.0016	−0.0063***	−0.0150***	−0.0189***
		(2.20)	(0.84)	(−1.08)	(−3.88)	(−9.75)	(−10.07)
	Macro alpha	−0.0498	−0.0743	−0.1105	−0.0573	−0.0556	−0.0059
		(−0.39)	(−0.68)	(−1.16)	(−0.56)	(−0.40)	(−0.05)
VW	Raw return	0.0154*	0.0201**	0.0170*	0.0147	0.0080	−0.0074**
		(1.79)	(2.19)	(1.85)	(1.50)	(0.85)	(−2.16)
	FF-5 alpha	−0.0002	0.0018	−0.0021	−0.0048**	−0.0112***	−0.0110***
		(−0.09)	(1.05)	(−1.19)	(−2.42)	(−5.11)	(−3.41)
	Macro alpha	0.0038	−0.0724	−0.0140	−0.0754	−0.0793	−0.0831
		(0.02)	(−0.53)	(−0.15)	(−0.56)	(−0.50)	(−0.40)

Note: This table displays the time-series average raw return, FF-5 alphas, and macro alphas on quintile portfolios ranked by alternative IVOL measures estimated from Fama and French (2015) five-factor model. The sample period is from January 2006 to June 2018. Newey–West t-statistics with four lags are shown in parentheses. The statistical significance at the 1%, 5%, and 10% levels are indicated with ***, **, and *, respectively.
Source: The Authors.

3.3.2. Alternative IVOL measure

Lehmann (1990) argue that the negative relation between idiosyncratic risk and expected returns may be caused by missing factors. To examine the missing factor explanation, DeLisle et al. (2016) estimated the alternative IVOL using an eight-factor model, including Fama and French (2015) five factors and the momentum factor, short-term return reversal factor, and long-term return reversal factor. In this subsection, we apply the Fama and French (2015) five-factor model to estimate the alternative IVOL measure as below:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_1 MKT_d + \beta_2 SMB_d + \beta_3 HML_d + \beta_4 RMW_d + \beta_5 CMA_d + \varepsilon_{i,d} \tag{10}$$

where $R_{i,d}$ is the daily return of stock i on day d, $R_{f,d}$ is the daily risk-free rate on day d, and MKT_d, SMB_d, HML_d, RMW_d, and CMA_d are the daily Fama and French (2015) five factors downloaded from the CSMAR Factor Research database.

The portfolio construction procedures are the same as in Section 3.1.1. Table 6 presents the time-series averages of raw returns, FF-5 alphas, and macro alphas of quintile portfolios ranked by alternative IVOL measures.

The results in Table 6 display similar patterns with that in Tables 2 and 5. The only exception is that for the alternative news IVOL, the FF-5 alphas of the EW and VW long-short portfolios become negative and statistically significant at convention level. However, it is still weaker than the negative price of IVOL and non-news IVOL.

In addition, after adjusting the raw returns by the additional five macroeconomic proxies, the risk adjusted returns on the long-short portfolios turn to insignificant, no matter sorted by IVOL, news IVOL, or non-news IVOL. In short, the results in Table 6 confirm the robustness of our above findings.

4. Conclusions

This study investigates the effect of firm-specific news and the news sentiment on the relation between IVOL and expected returns in the largest emerging market. The firm-specific news may play an influential role in disentangling the IVOL puzzle, given its impact on the variation of IVOL and mispricing. According to the limited arbitrage explanation, the negative premium of the IVOL around firm announcements is expected to be greater than the IVOL without news. However, we obtain contrasting findings after performing portfolio- and firm-level analysis. Such results indicate that the limited arbitrage may be not a perfect candidate to resolve the IVOL puzzle in China.

Furthermore, we find that under news context, the predictive ability of IVOL is stronger following bad news compared to good news. It indicates that bad news causes greater fluctuation in stock prices compared to good news, resulting in a greater negative price of IVOL. Ma et al. (2021) also report consistent findings that the Chinese security market reacts different to positive and negative news, and they explain this difference by the investors' attention bias.

Finally, when we include macroeconomic variables known to predict returns to adjust the systematic risk, we obtain striking findings that the negative premium of

IVOL becomes insignificant. These findings indicate that the negative premium of the IVOL portfolios is time-varying with macroeconomy, and the macroeconomic variables may contribute to disentangling the IVOL puzzle in the Chinese security market. Our results manifest that the common component in IVOL is related to the macroeconomy.

Our research also has some limitations. In this study, we only collect the firm-specific news data from the Event Research Database included in the CSMAR database. However, there are various types of news except firm-specific ones, such as macroeconomic news, industrial news, etc. Thus, future research could collect more types of news from multiple sources following Ma et al. (2021) and investigate their effects on market anomalies. In addition, the mechanism that how the macroeconomic factors drive the pricing power of IVOL also requires further investigation.

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