Journal of Banking and Finance 86 (2018) 240–258

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Limits of arbitrage and idiosyncratic volatility: Evidence from China stock market[☆]

Ming Gu [a,*], Wenjin Kang [b], Bu Xu [c]

[a] School of Economics & WISE, Xiamen University, China
[b] School of Finance, Shanghai University of Finance and Economics, China
[c] School of Economics and Management, Beijing University of Chemical Technology, China

ARTICLE INFO

Article history:
Received 7 October 2014
Accepted 8 August 2015
Available online 1 August 2016

JEL classification:
G12
G15

Keywords:
Limits of arbitrage
Idiosyncratic volatility
China stock market

ABSTRACT

This study examines how limits of arbitrage can affect the pricing of idiosyncratic volatility. Using both unique trading constraints in the Chinese stock market and other commonly-used limits-of-arbitrage measures, we construct a comprehensive limits-of-arbitrage index. Based on this index, we find that the negative idiosyncratic volatility return premium is much stronger and more persistent in stocks with high limits of arbitrage. Furthermore, the existing explanations about the idiosyncratic volatility return premium cannot fully explain what we find about the role of limits of arbitrage in the pricing of idiosyncratic volatility in the Chinese stock market. Our study suggests that the trading constraints introduced in the name of protecting individual investors can actually hurt them, since these additional limits of arbitrage will increase the inefficiency of the security market.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Ang et al. (2006, 2009) (hereafter referred to AHXZ (2006, 2009)) find a negative relation between idiosyncratic volatility (IVOL) and subsequent stock returns in U.S. and other developed equity markets. Their findings pose a challenge to the traditional rational asset pricing theory. Recent studies suggest that the negative relation between IVOL and subsequent stock returns could be possibly caused by: short-term return reversal (Huang et al., 2009; Fu, 2009), lottery-type stocks preference (Bali et al., 2011), arbitrage asymmetry (Stambaugh et al., 2015), and expected idiosyncratic skewness (Boyer et al., 2010).

In this study, we examine the negative return premium for high IVOL stocks from a new perspective, that is, limits of arbitrage. DeLong et al. (1990) indicates that noise traders can create an arbitrage risk by pushing the prices significantly away from fundamental values for an extended period of time. Shleifer and Vishny (1997) shows that arbitrage activity requires capital, and will become ineffective when market prices remain substantially deviated from fundamental values. Recent studies empirically examine the effect of limits of arbitrage on various market anomalies, including book-to-market effect (Ali et al., 2003), momentum and others (Nagel, 2005), accrual anomaly (Mashruwala et al., 2006), and asset growth anomaly (Lam and John Wei, 2011). Whenever a stock becomes mispriced, the arbitrage opportunity attracts rational investors to trade accordingly and earn their profits from the subsequent convergence of market price to fundamentals. However, there are certain types of limits of arbitrage that make the arbitrage process risky and costly in reality. Examples of limits of arbitrage include transaction cost, trading constraint, and information uncertainty. Transaction cost (or the low liquidity of stock) increases the cost of arbitrage strategy execution and makes it less attractive. Trading constraint, including short-selling constraint and other types of trading bans, will prevent arbitrageurs from exploiting market mispricing opportunities. When facing a high degree of information uncertainty, arbitrageurs become less willing to take risky positions. As a consequence of these impediments, market mispricing can persist and market efficiency will not be achieved instantaneously.

The underperformance of high IVOL stocks can be interpreted as a challenge to the market efficiency and a profit opportunity to arbitrageurs. As we argue above, limits of arbitrage, such as transaction costs, trading restrictions, and information uncertainty, can

☆ We thank Vincent Bogousslavsky, Harald Hau, Yi Huang, Ke Tang, Ran Tao, Hefei Wang, and Chengxi Yin as well as seminar participants at the 2014 Geneva-China Workshop in International Macroeconomics and Finance, and 2015 Frontiers of Business Research in China International Symposium, for their helpful comments and suggestions.

* Corresponding author. Address: School of Economics, Xiamen University, Xiamen, Fujian 361005, China.

E-mail address: calvingu2012@gmail.com (M. Gu).

https://doi.org/10.1016/j.jbankfin.2015.08.016
0378-4266/© 2015 Elsevier B.V. All rights reserved.

prevent arbitrageurs from exploiting this mispricing opportunity. Limits of arbitrage will become a more severe concern for overvalued stocks when short-selling is highly restricted, which is particularly true in the Chinese stock market. When arbitrageurs' hands are bound by these constraints, the price correction of overvalued stocks will take a longer period. Therefore, we expect to observe a stronger negative relation between idiosyncratic volatility and subsequent stock returns for stocks with high limits of arbitrage. Put this into other words, the negative IVOL premium should be less significant for stocks with low limits of arbitrage, since any mispricing profitability is easier to be exploited by arbitrageurs.

Following this logic, we employ a sample containing A-shares traded on the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) from January 2002 to December 2012 and examine the effect of limits of arbitrage on the pricing of idiosyncratic volatility in the Chinese stock market. We focus on the Chinese mainland stock market because there are some unique features such as price-limit rule and short-selling restrictions in China. Examples of these unique limits of arbitrage features include (i) price-limit rule: Since December 1996, the Chinese stock market has imposed the daily price change limit on trading of stocks. There is a 10% limit of daily price up or down for regular stocks. Investors cannot post limit buy (sell) order whose limit price is 10% higher (lower) than yesterday close price. In other words, when stocks hit the price-limit, the trading execution probability is low. In such circumstances, arbitrageurs have difficulty in buying or selling such stocks and there exists a higher level of limits of arbitrage; (ii) short-selling constraint: From March 2010, China Securities Regulatory Commission (CSRC) has introduced the margin trading and short selling (MTSS) program, which enables investors to borrow money and buy stocks, or to borrow stocks and short sell them. The number of stocks available for MTSS program increases as time goes on. Obviously, for stocks that are not included in this program, it will be very difficult, if not impossible, for arbitrageurs to short sell these stocks; (iii) the availability of index future: the China Securities Index 300 (CSI 300) future, which starts trading since April 2010, is the only tradable stock index future in the Chinese stock market. Arbitrageurs have incentive to hedge the market risk of their arbitrage positions by taking offsetting positions on the index future. We expect, for stocks that are not included the index, arbitrageurs will face a higher degree of limits of arbitrage. These unique stock trading policies in China provide us the opportunity to examine the effect of limits of arbitrage on the pricing of idiosyncratic volatility in more details. Besides these three Chinese unique limits of arbitrage features, we employ three additional commonly-used indicators, including stock illiquidity, trading volume, and analyst coverage. We first construct a comprehensive limits-of-arbitrage index by taking average of these six individual indicators, and then sort our sample stocks into low and high limits of arbitrage categories and examine the IVOL return premium in them separately.

Our main results are as follows. We find that a significant negative relationship between the idiosyncratic volatility and subsequent stock returns in the Chinese mainland stock market. The value-weighted (equally-weighted) risk-adjusted return difference between the highest and the lowest IVOL quintile portfolios is −1.09% (−1.76%) per month. Such monthly risk-adjusted return difference is amplified to −1.40% (−2.20%) when we examine the IVOL-based decile portfolios. This finding supplements AHXZ (2009) by providing the empirical evidence of negative IVOL return premium in a major emerging equity market.

More importantly, the negative premium of idiosyncratic volatility is much stronger in stocks with high limits of arbitrage. In practice, we examine the role of limits of arbitrage on IVOL premium by the following two-way sorting method: we first rank our sample stocks into tercile portfolios according to their comprehensive limits-of-arbitrage index, and then within each tercile we form five sub-portfolios based on their idiosyncratic volatility. We find a very substantial negative premium of idiosyncratic volatility in the high limits-of-arbitrage stock portfolio. The value- and equally-weighted risk-adjusted return differences between the highest and lowest IVOL quintile sub-portfolios in the high limits-of-arbitrage tercile are −2.18% and −2.29% per month. As a contrast, such monthly return differences in the low limits-of-arbitrage tercile are only −0.47% and −0.95%. When we consider the difference of IVOL return premium between the high and low limits-of-arbitrage stocks, the value- and equally-weighted IVOL return premium difference are −1.71% (t-statistic = −4.03) and −1.34% (t-statistic = −4.25) per month, respectively. This main finding is robust to alternative construction methods for the limits-of-arbitrage index.

We also take the observed IVOL negative premium and its relation with limits of arbitrage as an opportunity to examine whether the explanations proposed by previous studies for the pricing of idiosyncratic volatility in the U.S market can be applied to the Chinese stock market. First, we test the short-term return reversal explanation proposed by Huang et al. (2009). In the Fama–Macbeth return prediction regression, after including the previous-month stock return as a control for short-term return reversal, we are still able to find a significantly negative coefficient on the idiosyncratic volatility variable. Furthermore, we find that the IVOL negative premium is robust to a five-factor risk adjustment, which includes Fama–French three factors, momentum, and a short-term reversal factor. Therefore, it is unlikely for the short-term reversal to be the explanation for the IVOL negative premium observed in the Chinese stock market.

Second, Bali et al. (2011) shows a significantly negative relation between the lottery-type stock preference, which can be measured by the maximum daily return (or maximum five-day return) over past month, and expected stock returns, and suggest that this preference can explain the IVOL negative premium observed in the U.S. market. We adopt two-way (and three-way) dependent portfolio sorting method to examine whether the IVOL negative premium and its relation with limits of arbitrage is robust to the control of this preference. We find that, after controlling for the lottery-type stock preference, the risk-adjusted IVOL premium is still significantly negative, being −0.90% (−1.35%) per month for the value-weighted (equally-weighted) method. Moreover, after controlling for this preference, we still find that the IVOL premium is stronger among high limits-of-arbitrage stocks. As a sharp contrast, we find that, once the IVOL effect is controlled, there is no significant return difference between stocks with low and high lottery-like payoff features. Our analysis implies that idiosyncratic volatility plays a more important role in determining stock returns than lottery-like stock payoff features in the Chinese stock market.

Third, Stambaugh et al. (2015) argue that the negative IVOL return premium can be caused by an arbitrage asymmetry, that is, it is easier for investors to buy underpriced stocks than short-sell overpriced ones. Since mispricing is more severe for the overpriced side, the unconditional IVOL return premium is tilted towards a negative number. Following Stambaugh et al. (2015), we construct an overpricing/underpricing measure and examine whether this measure will affect the pricing of idiosyncratic volatility differently across stocks with different degree of limits of arbitrage. We find a significantly negative IVOL premium in the overpriced but not the underpriced stocks within the low limits-of-arbitrage tercile, which is consistent with what Stambaugh et al. (2015) find in the U.S. market. However, in the high limits-of-arbitrage tercile, the idiosyncratic volatility remains significantly negatively priced for both overpriced and underpriced stocks. [1] Therefore, the arbitrage asymmetry argument only provides a partial explanation to the IVOL premium observed in the Chinese stock market.

Our study contributes to the related literature in several aspects. First, we show that idiosyncratic volatility is significantly negatively priced in one of the most important emerging equity market – the Chinese stock market. Second, we find that the pricing of idiosyncratic volatility is related with the degree of limits of arbitrage, which suggests that the negative IVOL premium can be understood as an exhibition of market inefficiency. The higher the limits of arbitrage there are, the stronger IVOL premium we can observe. Third, our analysis suggests that the existing explanations proposed by previous studies about the IVOL negative premium, such as short-term return reversal, the lottery-like stock preference, and arbitrage asymmetry, cannot fully explain our findings. It underscores the importance of a better understanding about the pricing of idiosyncratic volatility and how it is related with limits of arbitrage in international markets. In other words, our study highlights the need for a better theoretical framework that can explain the IVOL premium observed in both developed market (e.g., U.S.) and emerging market (e.g., China), as well as the role of limits of arbitrage in this pricing mechanism. Fourth, the literature suggests that market anomalies are typically more significant in stocks with high limits of arbitrage. But most of the empirical evidence is from the U.S. market. We show that in the Chinese stock market, where there are additional unique trading restrictions due to the nature of an emerging market, high limits of arbitrage pose a particular concern to market efficiency. In fact, in the subsample of high limits-of-arbitrage portfolio, stocks with high IVOL underperform those with low IVOL by an annualized rate of 23%. Such mispricing opportunity can only exist when there are substantial limits of arbitrage in the market that prevent arbitrageurs to do their duty.

Our paper inherits the line of previous studies that examine how volatility is priced in the Chinese market. Drew et al. (2004) provide some evidence that high IVOL stocks underperform low IVOL stocks in the Chinese stock market in an earlier sample period of 1995–2000. Cakici et al. (2011) examine the return prediction power of several well-known return predictors in the Chinese stock market, and find that both high total and high idiosyncratic volatility measures can predict low subsequent stock returns. Nartea et al. (2013) also find a negative IVOL premium in the Chinese stock market, although they find no evidence of any long-term trend in the time series behavior of idiosyncratic volatility. Liu and Wang (2013) analyze the contemporaneous relationship between stock returns and idiosyncratic volatility. [2] Our paper differentiates with these studies by focusing on the effect of limits of arbitrage on the pricing of idiosyncratic volatility. We also test the existing explanations for the IVOL premium, such as short-term return reversal, lottery-like stock preference, and arbitrage asymmetry, and find that our results cannot be fully explained by them.

Our study also yields important policy implication. In emerging markets, certain types of trading constraints are often introduced in the name of protecting individual investors. However, these trading constraints usually add additional limits of arbitrage to the market, and as shown by our study, tend to make high idiosyncratic-volatility stocks more overvalued and followed by lower subsequent returns. Given the extant study about investors' trading pattern (e.g., Han and Kumar, 2013), retail investors are more likely to hold high idiosyncratic-volatility stocks. Therefore, the artificial trading constraints that are designed to protect them can actually hurt their welfare. Our study suggests that regulators should consider relaxing the unnecessary trading constraints to improve the market efficiency and better protect individual investors.

The remainder of the paper is organized as follows. Section 2 describes the sample and variables used in this study. Section 3 introduces the limits of arbitrage index and studies the effect of limits of arbitrage on the IVOL return premium. Section 4 provides extended analysis to examine possible explanations for the negative pricing of idiosyncratic volatility and the role of limits of arbitrage in this pricing mechanism in more detail. Section 5 concludes our paper.

2. Data and methodology

2.1. Summary statistics

Our sample contains all Chinese A-share firms listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange with available stock return and company balance-sheet data from China Stock Market and Accounting Research Database (CSMAR). The sample period spans from January 2002 to December 2012. [3] To make sure that all accounting variables are available, we match accounting data of fiscal year $t-1$ to the returns from July of year t to June of year $t+1$ [4] We exclude the financial firms and special treatment (ST) firms in the sample. [5]

Following AHXZ (2006), we calculate the idiosyncratic volatility ($IVOL_t$) of monthly stock return as the standard deviation of daily excess returns relative to Fama and French (1993) three-factor during month t. More specifically, stock i's idiosyncratic volatility in month t is calculated as below:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + \varepsilon_{i,d} \tag{1}$$

where $R_{i,d} - r_{f,d}$ is stock i's daily excess return on day d in month t, MKT_d, SMB_d, HML_d are daily returns of Fama and French (1993) three factors extracted from RESSET Financial Database.

We define RET_{t+1} as the monthly stock raw return in month $t+1$. Log of book-to-market ($lnBM_t$) is measured as the natural log of book to market equity at the end of last fiscal year. Log of size ($lnMV_t$) is measured as the natural log of market capitalization (in billion yuan) at the end of month t. $TURN_t$ is calculated as the turnover rate for the last six months. Following Bali et al. (2011), maximum daily return ($MAX5_t$) is calculated as the average of five highest daily returns within month t.

Table 1 presents the summary statistics and the correlation matrix. [6] Panel A of Table 1 reports the time-series average of

[1] We conjecture that the reason why the overpricing/underpricing measure becomes unrelated to the pricing of idiosyncratic volatility in the high limits-of-arbitrage subsample is that stocks with high limits of arbitrage tend to be overpriced in general. Actually, both the so-called "underpriced" and "overpriced" stocks within high limits-of-arbitrage tercile seem to be substantially overpriced based on their relative valuation ratio.

[2] We want to note that Liu and Wang (2013) examine the *contemporaneous* relationship with stock returns, instead of return prediction power, of idiosyncratic volatility. Therefore, their results are not directly comparable to the findings from our paper and other studies cited here.

[3] We consider the sample period starting from January 2002 for two reasons: (1) A-share firms started releasing quarterly reports since 2002, which is needed to construct the underpricing/overpricing measure; (2) We want to ensure there are an adequate number of stocks to form two-way or three-way sorted portfolios that are used in later sections.

[4] According to the regulations of China Securities Regulatory Commission (CSRC), any A-share firm must file the fiscal year report of year $t-1$ before April 30 at year t.

[5] 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.

[6] We produce the sample summary statistics following Fama–Macbeth two-step approach. In the first step we estimate the cross-sectional statistics of selected variables for each month. Then, in the second step, we calculate the time-series average and standard deviation of cross-sectional correlations obtained in the first step, and we conduct the corresponding confidence test based on these measures.

Table 1
Descriptive statistics. This reports the estimates of sample summary statistics following Fama–Macbeth two-step approach. In the first step, we estimate the cross-sectional statistics among selected variables for each month. Then, in the second step, we calculate the time-series average and standard deviation of cross-sectional statistics obtained in the first step, and we conduct the corresponding confidence test based on these measures. RET_{t+1} is the monthly raw return in month $t+1$ (in percent). Following AHXZ (2006), idiosyncratic volatility ($IVOL_t$) is calculated as the standard deviation of the daily residuals relative to Fama and French (1993) three-factor over month t. Log of book-to-market ($lnBM_t$) is measured as the natural log of book to market equity at the end of last fiscal year. Log of size ($lnMV_t$) is measured as the natural log of market capitalization (in billion yuan) at the end of month t. $TURN_t$ is the turnover for the last six months. As in Bali et al. (2011), maximum daily return ($MAX5_t$) is calculated as the average of five highest daily returns within month t. The full sample period is from January 2002 to December 2012. Panel A first estimates the cross-sectional mean, standard deviation, Q1, median value, and Q3 of selected variables for each month, and then reports the time-series average of these measures. Panel B first estimates the Pearson (above diagonal) and Spearman (below diagonal) cross-sectional correlations between variables, and then reports the time-series average of these correlations. The correlations that are significant at 5% significance level are expressed in bold font.

Panel A: descriptive statistics

	Mean	Std. Dev.	Q1	Median	Q3
RET_{t+1}(%)	1.34	9.26	−4.69	0.22	6.18
$IVOL_t$(%)	1.79	0.71	1.28	1.67	2.18
$lnBM_t$	−1.08	0.56	−1.40	−1.02	−0.69
$lnMV_t$	0.27	0.94	−0.39	0.15	0.80
$TURN_t$	2.79	1.68	1.69	2.43	3.46
$MAX5_t$	3.39	1.20	2.58	3.19	4.00

Panel B: correlation matrix

	RET_{t+1}	$IVOL_t$	$lnBM_t$	$lnMV_t$	TUR_t	$MAX5_t$
RET_{t+1}		**−0.07**	0.01	−0.02	**−0.03**	**−0.06**
$IVOL_t$	**−0.10**		**−0.15**	**−0.10**	**0.29**	**0.76**
$lnBM_t$	**0.02**	**−0.17**		**0.16**	**−0.08**	**−0.06**
$lnMV_t$	−0.03	**−0.08**	**0.16**		**−0.28**	**−0.06**
$TURN_t$	**−0.04**	**0.29**	**−0.10**	**−0.31**		**0.29**
$MAX5_t$	**−0.08**	**0.72**	**−0.08**	**−0.05**	**0.30**	

the cross-sectional mean, standard deviation, 25 percentile, median and 75 percentile statistics of the variables introduced above. The average monthly stock-level return is 1.34% and its median is 0.22%, indicating a right skewness in its distribution. The mean of stock idiosyncratic volatility is 1.79% and its median is 1.67%.

Panel B reports the time-series average of the cross-sectional Pearson and Spearman correlation estimates. The Pearson (Spearman) correlation between the next month return and idiosyncratic volatility is significantly negative, being −0.07 (−0.10), which confirms the negative return premium of IVOL in the univariate test. The correlations between the next month return and size (book-to-market) have consistent expected signs. Turnover is negatively related to the next month return, suggesting a return premium for low turnover (illiquid) stocks. Similar to Bali et al. (2011), maximum daily return is highly positively correlated with idiosyncratic volatility (Pearson = 0.76, Spearman = 0.72). We use maximum daily return to control the influence of lottery-type stocks preference.

2.2. One-way portfolio sorting on idiosyncratic volatility

In this section, we directly sort stocks based on their idiosyncratic volatility and examine the performance of each IVOL portfolio. At the end of month t, stocks are sorted into quintiles based on their monthly IVOL. P5 includes stocks with the highest IVOL in month t and P1 contains stocks with the lowest IVOL. To further examine the return pattern among different IVOL levels, we report the decile-portfolio sorting results as well.

In Table 2, Panel A reports the raw returns and Fama and French (1993) three factor risk adjusted returns for each quintile portfolio, and the average return spreads between P5 and P1. The results show that portfolios with higher IVOL generally have lower returns. The value-weighted return difference (P5–P1) are significantly negative for both raw returns (−1.02% per month with t-statistic = −2.60) and risk adjusted returns (−1.09% per month with t-statistic = −3.14). We find the same pattern when considering the equally-weighted average returns. The return spreads are economically substantial and statistically significant at 1% level (−1.79% per month with t-statistic = −7.63 and −1.76% per month with t-statistic = −8.05 for raw returns and risk adjusted returns, respectively).

In Panel B, when decile IVOL portfolios are formed, the monthly return difference between portfolios D10 and D1 are even larger, as expected. For value-weighted portfolios, the zero-cost trading strategy of buying D10 and shorting D1 yields the average raw return of −1.32% (t-statistic = −2.77) and the average risk adjusted return of −1.40% (t-statistic = −3.37) per month. For equally-weighted results, the raw return difference is −2.21% (t-statistic = −7.51) and the risk adjusted return is −2.20% (t-statistic = −7.84), significant at 1% level.

Comparing the IVOL premium observed in China market with those documented in AXHZ (2009), we find that the monthly return difference between high and low IVOL stock portfolios in the Chinese stock market is larger than in developed markets. In an ideal setting, when arbitrage opportunities can be exploited at little risk and zero cost, rational investors can short-sell stocks with high IVOL and buy stocks with low IVOL aggressively. As a result, the IVOL market anomaly will be arbitraged away in a timely manner. However, as we have discussed above, the implementations of arbitrage are often risky and costly in real markets. Higher limits of arbitrage make it more difficult for arbitrageurs to take advantage of the IVOL anomaly. Chinese stock market tends to have more trading constraints than developed markets, and these additional limits of arbitrage can impede arbitrageurs' ability to trade on the mispricing opportunity and bring market back to efficiency. Therefore, it is not a surprise to observe a stronger IVOL anomaly in the Chinese stock market. Furthermore, we can form the hypothesis that the negative return premium of idiosyncratic volatility should be more significant in stocks with higher limits of arbitrage in China market. This hypothesis will be tested in the following section.

3. The effect of limits of arbitrage on the pricing of idiosyncratic volatility

This section explores the interaction of limits of arbitrage and the pricing of idiosyncratic volatility. In the first subsection, we introduce a comprehensive limits-of-arbitrage index. In the second subsection, we form double-sorted portfolios based on this limits-of-arbitrage index and idiosyncratic volatility, and test whether the idiosyncratic volatility return premium becomes more negative in stocks with higher limits of arbitrage. In the third subsection, we conduct robustness tests based on alternative definitions of the limits-of-arbitrage index. In the fourth subsection, we examine the persistence of the influence of limits of arbitrage on IVOL premium. In the fifth subsection, we run Fama and MacBeth (1973) cross-sectional regressions to examine how the IVOL's return-predicting power is affected by the limits-of-arbitrage index.

3.1. The limits-of-arbitrage index

We propose a comprehensive limits-of-arbitrage index that includes information from six individual limits-of-arbitrage indicators. Notably, the first three indicators – price-limit-hitting, the

Table 2
Portfolio sorting based on idiosyncratic volatility. We form the value-weighted (VW) and equally-weighted (EW) quintile and decile portfolios every month based on idiosyncratic volatility. In Panel A, at the end of month t, stocks are sorted into quintiles based on their idiosyncratic volatility (IVOL) over month t, from the lowest (P1) to the highest idiosyncratic volatility (P5). In month $t+1$, the average raw returns and Fama and French (1993) three-factor risk adjusted returns of each quintile portfolio are reported (in percent). The same procedure is repeated in Panel B except that we sort stocks into decile portfolios. The full sample period is from January 2002 to December 2012; t-statistics are in parentheses.

Panel A: quintile portfolios sorting based on IVOL

	P1	P2	P3	P4	P5	P5–P1	*t-stat*
VW raw return	1.29	1.23	1.45	0.88	0.27	−1.02	(*−2.60*)
VW risk adjusted returns	0.17	0.08	0.30	−0.26	−0.92	−1.09	(*−3.14*)
EW raw return	2.05	1.85	1.65	1.19	0.27	−1.79	(*−7.63*)
EW risk adjusted returns	0.61	0.38	0.20	−0.28	−1.15	−1.76	(*−8.05*)

Panel B: decile portfolios sorting based on IVOL

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10–D1	*t-stat*
VW raw return	1.32	1.37	1.17	1.38	1.53	1.34	1.00	0.77	0.51	−0.01	−1.32	(*−2.77*)
VW risk adjusted returns	0.21	0.23	0.01	0.23	0.34	0.22	−0.13	−0.41	−0.68	−1.19	−1.40	(*−3.37*)
EW raw return	2.06	2.05	1.89	1.81	1.73	1.58	1.41	0.97	0.69	−0.16	−2.21	(*−7.51*)
EW risk adjusted returns	0.62	0.60	0.39	0.36	0.24	0.15	−0.06	−0.50	−0.73	−1.58	−2.20	(*−7.84*)

availability of short-selling, and the availability of index future – are unique features in the Chinese stock market. The other three indicators, stock illiquidity, trading volume, and analyst coverage, are more commonly-used in previous studies. The exact definition of each individual indicator is provided in the appendix Table A1. In the following paragraphs, we first discuss these six limits of arbitrage indicators one-by-one, and then introduce how we construct the limits-of-arbitrage index.

The first limits of arbitrage indicator is price-limit-hitting. Since December 1996, the Chinese stock market has imposed the daily price-limit rule on stock trading. There is a 10% limit of daily price up or down for regular stocks and a 5% limit for stocks under special treatment. When a stock hits its daily up (down) limit, the trading execution will happen only if someone posts a sell (buy) order with a price equal to or lower (higher) than its daily up (down) limit price. Kim and Ghon Rhee (1997) shows that price-limit rules can cause delays in equilibrium price discovery. Intuitively, stocks that hit the price limit more often are more likely to face higher limits of arbitrage.

The second indicator is the availability of short-selling. Margin trading and short selling (MTSS), is a pilot program in the Chinese stock market initiated in March 2010. MTSS selects a subset of A-share stocks and enables investors to borrow money and buy the underlying stocks, or to borrow stocks and short sell them. Jones and Lamont (2002) and Asquith et al. (2005) suggest that whether short sellers can profit from short-selling depends on implementation costs, including the supply of shares to borrow. We expect that stocks included in MTSS program bear less short-selling constraints, while stocks that are not included in MTSS program are exposed to higher limits of arbitrage since it will be very difficult, if not impossible, to short-sell such stocks.

The third indicator is the availability of index future. China Securities Index 300 (CSI 300) selects the largest 300 stocks, which can best represent the China economy activity, from the listed A-share stocks. CSI 300 index future, listed on April 2010, is the only tradable stock market index future in the Chinese market. Arbitrageurs have incentive to hedge the market risk of their arbitrage positions by taking offsetting positions on the index future. We expect, for stocks that are not included the index, arbitrageurs will face a higher degree of limits of arbitrage.

We also introduce three other indicators that are commonly-used in the related literature – stock illiquidity, trading volume, and analyst coverage. For instance, Sadka and Scherbina (2007) argue that increases in liquidity reduce the costs of arbitrage and accelerate the convergence of prices to fundamentals. Chordia et al. (2008) indicate that liquidity stimulates arbitrage activity, which enhances the market efficiency. Mashruwala et al. (2006) argue that greater trading volume is associated with lower trading costs and enables traders to find the counterparty of their trades more easily. Hong et al. (2000) show that stocks with lower analyst coverage are associated with more slowly information dissemination. Hence, we expect that stocks with higher illiquidity, lower trading volume, and less analyst coverage have higher limits of arbitrage.

Since each of the indicators introduced above captures different dimensions of limits of arbitrage, we believe that an aggregate limits-of-arbitrage index, combining all these six indicators, should provide a more comprehensive proxy of limits of arbitrage for stocks listed on China market. In each month, for a given indicator, we assign the value of one for the stocks about which high limits of arbitrage are recognized, and zero otherwise. More specifically, price-limit-hitting will be assigned the value of one for stock i if it reaches at daily price limit for at least once in month t; the availability of short-selling or the availability of index future will be assigned the value of one if the stock is short-sellable or included in the CSI300 index. The illiquidity measure will be assigned the value of one if stock i's illiquidity is larger than the cross-sectional median in month t; the trading volume or analyst coverage measure will be assigned the value of one if the corresponding value is below or equal to the cross-sectional median. We consider the dummy variable approach because the unique trading restrictions in the Chinese stock market have binomial status. For example, investors either can or cannot do short selling on a given stock. Then we average all available limits-of-arbitrage indicator dummy variables for a stock to produce its limits-of-arbitrage index (with the requirement that a minimum of two indicators are available). By its definition, the value of this index spans from zero to one, and higher value of the index indicates higher limits of arbitrage to the particular stock. The cross-sectional distribution of the limits-of-arbitrage index is described in the appendix Table A2. As we can observe from the table, there is an approximate uniform distribution of the index value from zero to one.

3.2. Two-way portfolios sorting on limits of arbitrage and idiosyncratic volatility

Once we have constructed the limits-of-arbitrage index as described above, we examine how limits of arbitrage can affect the pricing of idiosyncratic volatility. We expect the IVOL negative return premium is stronger in high limits-of-arbitrage stocks than in low limits-of-arbitrage stocks. In this subsection we employ a two-way dependent portfolio sorting method to test this hypothesis.

More specifically, we form 3 * 5 portfolios every month based on the limits-of-arbitrage index and stock idiosyncratic volatility. First, we categorize stocks into terciles – low, medium, and high

Table 3
Portfolio sorting by limits of arbitrage and idiosyncratic volatility. We form a two-way portfolio sorting by limits of arbitrage and idiosyncratic volatility. First, we categorize stocks into terciles based on their limits-of-arbitrage index in month *t*. The index is the average of six limits-of-arbitrage indicators, consisting of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details). Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility over month *t*, from the lowest (P1) to the highest (P5) idiosyncratic volatility. In month $t+1$, the average raw returns and Fama and French (1993) three-factor adjusted returns of each portfolio are reported (in percent). The sample period is from January 2002 to December 2012; *t*-statistics are in parentheses.

	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.09	1.26	1.35	1.16	0.66	−0.43	(−*0.99*)
Medium limits of arbitrage	1.78	1.59	1.34	0.75	0.13	−1.65	(−*4.70*)
High limits of arbitrage	2.52	2.17	1.83	1.14	0.17	−2.35	(−*8.52*)
High–low						−1.92	(−*4.31*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.11	0.21	0.32	0.16	−0.37	−0.47	(−*1.19*)
Medium limits of arbitrage	0.36	0.21	−0.01	−0.58	−1.17	−1.53	(−*4.66*)
High limits of arbitrage	0.88	0.55	0.21	−0.41	−1.30	−2.18	(−*8.42*)
High–low						−1.71	(−*4.03*)
Equally-weighted raw returns							
Low limits of arbitrage	1.48	1.51	1.36	0.96	0.49	−0.99	(−*3.15*)
Medium limits of arbitrage	2.13	1.84	1.54	1.03	0.04	−2.09	(−*7.62*)
High limits of arbitrage	2.71	2.33	2.01	1.34	0.31	−2.40	(−*9.33*)
High–low						−1.41	(−*4.34*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.22	0.22	0.07	−0.28	−0.73	−0.95	(−*3.40*)
Medium limits of arbitrage	0.64	0.35	0.09	−0.44	−1.36	−2.01	(−*7.66*)
High limits of arbitrage	1.04	0.66	0.34	−0.29	−1.25	−2.29	(−*9.13*)
High–low						−1.34	(−*4.25*)

limits-of-arbitrage stocks – based on their limits-of-arbitrage index calculated in month *t*. Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility in month *t*, from the lowest (P1) to the highest (P5) idiosyncratic volatility portfolio. In month $t+1$, we observe the value-weighted and equally-weighted average stock raw returns and Fama and French (1993) three-factor risk adjusted returns of each portfolio, which are reported in Table 3.

The results in Table 3 confirm our hypothesis: the idiosyncratic volatility premium is stronger among stocks with higher limits of arbitrage. For stocks with high limits of arbitrage, the value-weighted monthly return difference between the high and low IVOL portfolios is −2.35% (*t*-statistic = −8.52) for raw returns and −2.18% (*t*-statistic = −8.42) for Fama–French three-factor risk adjusted returns. As a sharp contrast, the IVOL return premium becomes much weaker, or even insignificant, in stocks with low limits of arbitrage: the value-weighted return difference between high and low IVOL stocks is −0.43% per month (*t*-statistic = −0.99) for raw returns and −0.47% per month (*t*-statistic = −1.19) for Fama–French three-factor risk adjusted returns.

We also consider a difference-of-difference test, in which we examine whether the IVOL return premium, which is defined as the return difference between the high and low idiosyncratic volatility stocks, obtained in high and low limits-of-arbitrage portfolios are significantly different from each other. The difference of IVOL return premium based on the value-weighted method between high and low limits-of arbitrage tercile portfolios are significantly negative in both raw returns (−1.92% per month with *t*-statistic = −4.31) and Fama–French three-factor risk adjusted returns (−1.71% per month with *t*-statistic = −4.03). The empirical results based on the equally-weighted method are similar – the difference of IVOL return premium between high and low limits-of-arbitrage tercile portfolios is −1.41% per month (*t*-statistic = −4.34) for raw returns and −1.34% per month (*t*-statistic = −4.25) for Fama–French three-factor risk adjusted returns.

Overall, we find that the negative return premium of high idiosyncratic volatility stocks is more prominent in the high limits-of-arbitrage portfolio. This finding suggests that the IVOL premium can be interpreted as an exhibition of market inefficiency. High limits of arbitrage drag the market further away from the efficient status, and as a result, high idiosyncratic volatility stocks can get more overpriced and deliver lower subsequent returns.

3.3. Robustness tests based on alternative definitions of the limits-of-arbitrage index

In this subsection, we conduct robustness tests based on alternative definitions of the limits-of-arbitrage index. As a starting point, we examine the correlations among our six individual limits-of-arbitrage indicators, and find that they are positively correlated with each other in general, as shown in the appendix Table A3. This highlights the need of additional robustness tests for our main results. In this sub-section, we adopt three alternative definitions of the limits-of-arbitrage index, and show that our main findings hold for each of them.

First, we split our six individual limits-of-arbitrage indicators into two groups, with three indictors in each group. More specifically, we put price-limit-hitting, the availability of index future, and illiquidity indicators into the first group, and the availability of margin trading and short-selling, trading volume, and analyst coverage indicators into the second group. In Panel A of Table 4, we present the result from two-way portfolio sorting based on IVOL and the limits-of-arbitrage index, which is constructed from the first group of indicators as introduced above. Panel B of Table 4 presents similar results from the second group of indictors as introduced above. In both panels, we find that IVOL negative premium is more prominent in high limits-of-arbitrage stocks than in low limits-of-arbitrage stocks.

Second, we split our six individual limits-of-arbitrage indicators into three groups instead, with two indictors in each group. In other words, we construct three limits-of-arbitrage indexes in this approach, and repeat our analysis for each of them. For the

Table 4

Portfolio sorting by limits of arbitrage and idiosyncratic volatility (by the index consisting of three limits-of-arbitrage indicators). We form a two-way portfolio sorting by limits of arbitrage and idiosyncratic volatility. First, we categorize stocks into terciles based on their limits-of-arbitrage index in month t. The index is the average of three limits-of-arbitrage indicators. In each panel, we choose three out of total six limits-of-arbitrage indicators. The six indicators consist of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details).Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility over month t, from the lowest (P1) to the highest (P5) idiosyncratic volatility. In month $t+1$, the average raw returns and Fama and French (1993) three-factor risk adjusted returns of each portfolio are reported (in percent). The sample period is from January 2002 to December 2012; t-statistics are in parentheses.

Panel A: index consisting of price-limit-hitting, the availability of index future, and illiquidity

	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.28	1.33	1.47	1.26	0.54	−0.74	(*−1.69*)
Medium limits of arbitrage	1.21	1.18	1.19	0.81	0.01	−1.20	(*−3.09*)
High limits of arbitrage	2.44	1.98	1.59	0.85	0.32	−2.12	(*−7.12*)
High–low						−1.38	(*−3.20*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.24	0.29	0.44	0.22	−0.51	−0.75	(*−1.90*)
Medium limits of arbitrage	−0.04	−0.14	−0.11	−0.42	−1.18	−1.14	(*−3.12*)
High limits of arbitrage	0.92	0.52	0.17	−0.58	−1.06	−1.98	(*−6.76*)
High–low						−1.23	(*−3.09*)
Equally-weighted raw returns							
Low limits of arbitrage	1.60	1.62	1.39	1.09	0.27	−1.33	(*−4.43*)
Medium limits of arbitrage	2.21	1.82	1.57	1.14	0.10	−2.11	(*−7.92*)
High limits of arbitrage	2.65	2.23	1.88	1.24	0.24	−2.41	(*−9.06*)
High–low						−1.08	(*−3.64*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.28	0.28	0.08	−0.20	−1.04	−1.32	(*−4.72*)
Medium limits of arbitrage	0.71	0.31	0.11	−0.33	−1.26	−1.98	(*−8.34*)
High limits of arbitrage	1.04	0.62	0.29	−0.35	−1.28	−2.32	(*−8.76*)
High–low						−1.00	(*−3.46*)

Panel B: index consisting of the availability of margin trading and short-selling, trading volume, and analyst coverage

	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.11	1.24	1.59	1.03	0.45	−0.66	(*−1.45*)
Medium limits of arbitrage	1.63	1.43	1.31	0.87	0.13	−1.50	(*−4.71*)
High limits of arbitrage	2.22	2.02	1.87	0.96	0.22	−2.00	(*−6.45*)
High–low						−1.34	(*−3.11*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.12	0.23	0.57	0.05	−0.58	−0.69	(*−1.68*)
Medium limits of arbitrage	0.25	0.00	−0.07	−0.54	−1.21	−1.45	(*−4.96*)
High limits of arbitrage	0.71	0.47	0.36	−0.60	−1.29	−2.01	(*−6.45*)
High–low						−1.31	(*−3.16*)
Equally-weighted raw returns							
Low limits of arbitrage	1.47	1.54	1.55	0.92	0.44	−1.03	(*−3.06*)
Medium limits of arbitrage	2.12	1.80	1.56	1.11	0.15	−1.97	(*−8.22*)
High limits of arbitrage	2.61	2.26	2.03	1.25	0.38	−2.23	(*−8.89*)
High–Low						−1.19	(*−3.52*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.23	0.28	0.30	−0.31	−0.78	−1.00	(*−3.29*)
Medium limits of arbitrage	0.60	0.28	0.09	−0.40	−1.30	−1.90	(*−8.33*)
High limits of arbitrage	0.98	0.60	0.40	−0.40	−1.20	−2.18	(*−8.71*)
High–low						−1.18	(*−3.62*)

conciseness of our paper, the results of this part are presented in the appendix Table A4. For each of three indexes constructed here, we are able to find a more negative IVOL premium for high limits-of-arbitrage stocks.

Third, we consider another robustness test in which we re-do our analysis for six times. In each round of robustness test, we exclude one out of the six individual indicators for the index composition. In other words, we obtain six different versions of limits-of-arbitrage indexes in this approach, and conduct our analysis for each of them. The results from these six rounds of robustness test are reported in Table 5. Again, we find similar results from these six rounds of robustness test in Table 5.

Overall, for all these alternative definitions of limits-of-arbitrage indexes considered in our robustness tests, we are always able to find that the IVOL negative premium is stronger for high limits-of-arbitrage stocks.

3.4. The persistence of the influence of limits of arbitrage on IVOL premium

In this sub-section we extend our analysis of the profitability of IVOL-based trading strategy to a longer holding period (up to 6 months) within the high, medium, and low limits-of-arbitrage terciles, respectively. We find that the IVOL premium difference between high and low limits-of-arbitrage terciles keeps widening to a larger magnitude when we consider longer holding periods, which suggests that the IVOL return premium is not only larger but also more persistent for stocks with high IVOL than those with low IVOL. More specifically, In Table 6, we show that within low limits-of-arbitrage portfolio, the cumulative value-weighted raw return (risk-adjusted return) difference between high and low IVOL stocks increases from −0.43% (−0.47%) in month $t+1$ to −1.03% (−0.85%) in month $t+6$. For the high limits-of-arbitrage portfolio, the cu-

Table 5
Portfolio sorting by limits of arbitrage and idiosyncratic volatility (by the index consisting of five limits-of-arbitrage indicators). We form a two-way portfolio sorting by limits of arbitrage and idiosyncratic volatility. First, we categorize stocks into terciles based on their limits-of-arbitrage index in month *t*. The index is the average of five limits-of-arbitrage indicators. In each panel, we choose five out of six limits-of-arbitrage indicators. The six indicators consist of price-limit-hitting, the availability of margin trading and short-selling (MTSS), the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details). Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility over month *t*, from the lowest (P1) to the highest (P5) idiosyncratic volatility. In month *t* + 1, the average raw returns and Fama and French (1993) three-factor risk adjusted returns of IVOL premium are reported (in percent). The sample period is from January 2002 to December 2012; *t*-statistics are in parentheses.

	Excluding the price-limit-hitting		Excluding the availability of MTSS		Excluding the availability of index future		Excluding the illiquidity		Excluding the trading volume		Excluding the analyst coverage	
	P5–P1	*t-stat*	P5–P1	*t-stat*	P5–P1	*t-stat*	P5–P1	*t-stat*	P5–P1	*t-stat*	P5–P1	*t-stat*
Value-weighted raw returns												
Low	−0.68	(−1.53)	−0.42	(−0.97)	−0.41	(−0.94)	−0.59	(−1.37)	−0.62	(−1.44)	−0.59	(−1.42)
Medium	−1.53	(−5.05)	−1.65	(−4.69)	−1.62	(−4.53)	−1.48	(−3.71)	−1.55	(−4.03)	−1.64	(−4.04)
High	−1.99	(−7.79)	−2.35	(−8.48)	−2.33	(−8.50)	−2.55	(−8.41)	−2.24	(−8.68)	−2.51	(−8.21)
High–low	−1.31	(−3.02)	−1.92	(−4.32)	−1.92	(−4.29)	−1.96	(−4.69)	−1.62	(−3.99)	−1.91	(−4.63)
Value-weighted risk adjusted returns												
Low	−0.73	(−1.80)	−0.47	(−1.18)	−0.45	(−1.14)	−0.61	(−1.56)	−0.68	(−1.73)	−0.60	(−1.60)
Medium	−1.51	(−5.17)	−1.53	(−4.65)	−1.50	(−4.46)	−1.27	(−3.36)	−1.45	(−3.89)	−1.45	(−3.67)
High limits	−1.90	(−7.83)	−2.18	(−8.38)	−2.16	(−8.39)	−2.39	(−8.43)	−2.12	(−8.61)	−2.26	(−8.49)
High–low	−1.17	(−2.79)	−1.71	(−4.03)	−1.71	(−4.03)	−1.78	(−4.44)	−1.44	(−3.74)	−1.66	(−4.31)
Equally-weighted raw returns												
Low	−1.23	(−3.74)	−0.98	(−3.11)	−0.97	(−3.08)	−0.96	(−3.29)	−1.19	(−3.97)	−1.10	(−3.74)
Medium	−1.90	(−7.75)	−2.09	(−7.63)	−2.10	(−7.59)	−1.98	(−7.02)	−2.13	(−7.58)	−2.13	(−7.43)
High	−2.12	(−8.79)	−2.40	(−9.33)	−2.39	(−9.34)	−2.67	(−9.90)	−2.34	(−9.76)	−2.52	(−9.23)
High–low	−0.89	(−2.77)	−1.42	(−4.35)	−1.42	(−4.35)	−1.71	(−5.50)	−1.15	(−3.94)	−1.41	(−4.40)
Equally-weighted risk adjusted returns												
Low	−1.20	(−4.14)	−0.94	(−3.36)	−0.94	(−3.33)	−0.92	(−3.47)	−1.17	(−4.25)	−1.08	(−4.14)
Medium	−1.90	(−7.83)	−2.01	(−7.68)	−2.01	(−7.63)	−1.83	(−6.91)	−2.05	(−7.80)	−1.99	(−7.22)
High	−2.07	(−8.79)	−2.30	(−9.13)	−2.29	(−9.14)	−2.56	(−9.74)	−2.27	(−9.60)	−2.38	(−9.08)
High–low	−0.86	(−2.74)	−1.35	(−4.27)	−1.35	(−4.28)	−1.64	(−5.33)	−1.11	(−3.86)	−1.29	(−4.13)

Table 6
Cumulative returns spreads of limits-of-arbitrage portfolios. At the end of each month, we sort stocks into terciles by limits-of-arbitrage index. Within each tercile, we further sort stocks into quintiles by idiosyncratic volatility, and form a portfolio by longing P5 (the highest IVOL) and shorting P1 (the lowest IVOL). The portfolios are holding up to 6 months, from month *t* + 1 to month *t* + 6. For three limits-of-arbitrage portfolios, the cumulative value-weighted average raw returns and Fama and French (1993) three-factor risk adjusted returns spreads (P5–P1) are calculated at the end of each month. The sample period is from January 2002 to December 2012; Newey and West (1987) robust *t*-statistics with 4 lags are in parentheses.

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Raw return						
Low limits of arbitrage	−0.43	−0.67	−0.88	−1.26	−1.16	−1.03
Medium limits of arbitrage	−1.65	−2.54	−2.83	−3.73	−3.99	−4.36
High limits of arbitrage	−2.35	−3.37	−3.96	−4.40	−4.63	−4.96
High–low	−1.92	−2.69	−3.08	−3.14	−3.47	−3.93
t-stat	(−3.95)	(−2.88)	(−2.36)	(−2.04)	(−2.03)	(−2.10)
Fama–French three-factor adjusted returns						
Low limits of arbitrage	−0.47	−0.60	−0.64	−0.71	−0.64	−0.85
Medium limits of arbitrage	−1.53	−2.22	−2.27	−2.93	−3.01	−3.53
High limits of arbitrage	−2.18	−2.98	−3.46	−3.98	−3.93	−4.19
High–low	−1.71	−2.38	−2.82	−3.27	−3.29	−3.34
t-stat	(−3.84)	(−3.13)	(−2.62)	(−2.42)	(−1.99)	(−1.73)

mulative value-weighted raw return (risk-adjusted return) difference between high and low IVOL stocks increases from −2.35% (−2.18%) in month *t* + 1 to −4.96% (−4.19%) in month *t* + 6. In other words, the difference of IVOL return premium between high and low limits-of-arbitrage portfolios widens from −1.92% (−1.71%) in month *t* + 1 to −3.93% (−3.34%) in month *t* + 6 for the raw return (risk-adjusted return). To address the potential econometrics concern of *t*-statistics being inflated by the overlapping holding periods used when calculating portfolio returns, we use the Newey–West adjusted standard errors to estimate the *t*-statistics for the cumulative returns of our IVOL and limits-of-arbitrage portfolios.

Fig. 1 provides a more vivid illustration of the cumulative risk-adjusted return difference between stocks with high and low IVOL within each of the three limits-of-arbitrage portfolios. The solid line, dash line, and dot line represent the cumulative IVOL return premium (adjusted by the Fama–French three-factor model) in low, medium, and high limits-of-arbitrage stocks, respectively. The IVOL return premium obtained within low limits-of-arbitrage stocks stays flat after month *t* + 2, but the same premium obtained within medium and high limits-of-arbitrage portfolios keep moving downward until month *t* + 6. Altogether, here we show that, when compared with low limits-of-arbitrage stocks, the negative IVOL premium is more persistent in high limits-of-arbitrage stocks.

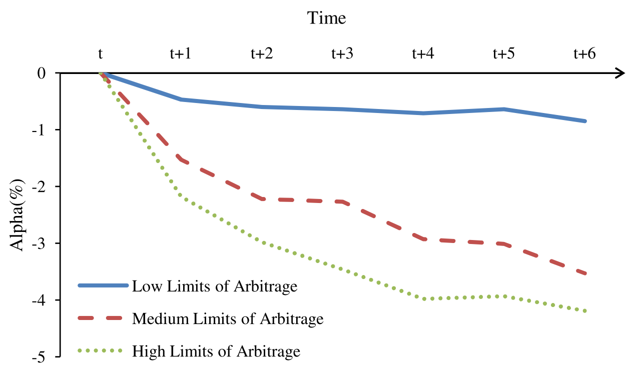

Fig. 1. Cumulative Fama–French three-factor risk adjusted returns spreads. The figure plots the cumulative Fama and French (1993) three-factor risk adjusted IVOL return premium of low, medium, and high limits-of-arbitrage portfolios. At the end of month t, we sort stocks into terciles by limits-of-arbitrage index. Within each tercile, we further sort stocks into quintiles by idiosyncratic volatility and form a portfolio by longing P5 (the highest IVOL) and shorting P1 (the lowest IVOL). The portfolios are holding up to 6 months, from month $t+1$ to month $t+6$. The cumulative value-weighted average risk adjusted returns spreads (P5–P1) of three limits-of-arbitrage portfolios are calculated at the end of each month. The sample period is from January 2002 to December 2012.

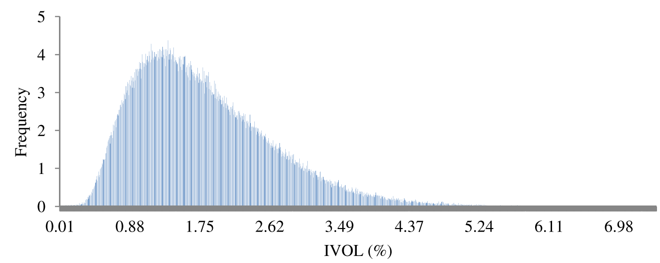

Fig. 2. Histogram of idiosyncratic volatility. The figure plots the average cross-sectional histogram of idiosyncratic volatility (IVOL). The sample period is from January 2002 to December 2012.

3.5. Fama–MacBeth regression

In this subsection, we re-examine the role of limits of arbitrage in the pricing of idiosyncratic volatility by employing Fama and MacBeth (1973) cross-sectional regression method. Following AHXZ (2009) and Han and Lesmond (2011), we report the value-weighted Fama–MacBeth regression results, using one-month-lagged firm size as the weight, to reduce the influence of small stocks on our analysis. [7] We run the cross-sectional regression of firm excess returns in month $t+1$ ($EXRET_{i,t+1}$) on the idiosyncratic volatility of month $t(IVOL_{i,t})$, the interaction terms of IVOL and dummy variables based on the limits-of-arbitrage index, together with other control variables. We then report the time-series average of the cross-sectional regression coefficient estimates and the associated t-statistics.

Following Mashruwala et al. (2006), we use the scaled monthly decile rank for explanatory variables with the superscript “ran” in the regression. For example, in every month, we rank the idiosyncratic volatility ($IVOL_{i,t}$) of each firm into deciles. The ranks are then transformed so that each observation of the variable takes the value ranging between −0.5 and 0.5. More specifically, the ranks are obtained as follows: every month we assign a decile rank to each variable from one to ten, and then transform this rank by subtracting one and dividing by nine. Finally, we subtract 0.5 from each of these transformed ranks in order to get ranks ranging from −0.5 to 0.5.

The ranking variable approach is employed for the following reasons. First, we scaled the independent variables to avoid the potential for difficulties with outliers (Bernard and Thomas, 1990). As illustrated in Fig. 2 , we examine the distribution of stock idiosyncratic volatility (IVOL). We find that the skewness of IVOL is 0.96 and the kurtosis of IVOL is 4.16, in which the large third and fourth moments of IVOL suggest that stock idiosyncratic volatility has positive skewness and fat-tail distribution. Therefore, there may exist an extreme value concern. Second, we rank the firm-characteristic variables to make regression coefficients comparable across characteristics (Bessembinder and Zhang, 2013). Given the way we have constructed the regressions, the coefficient on the independent variable can be interpreted as the premium from the zero-cost portfolio formed on the regressor variable (Mashruwala et al., 2006). The coefficient on the interaction term of IVOL and limits of arbitrage represents the additional spread in returns, between the lowest IVOL and highest IVOL stocks, for observations across different limits-of-arbitrage portfolios.

The dummy variable $LOW_{i,t}/MEDIUM_{i,t}/HIGH_{i,t}$ is assigned one if the stock i belongs to the bottom/middle/top tercile based on the limits-of-arbitrage index in month t. The coefficient estimates of the interactive item of IVOL and these dummy variables are the focus of our analysis here. We also apply the ranking value approach to the control variables, including $lnMV$, $lnBM$, $TURN$, $XRET$, and $MAX5$.

We consider three specifications of Fama–MacBeth regression and present the regression results in Table 7. In the first specification, we run the regression of returns on idiosyncratic volatility with other control variables. The coefficient of $IVOL^{ran}_{i,t}$ (−1.08 with t-statistic = −2.87) is significantly negative, showing that the IVOL puzzle is robust after controlling for return reversals, size ef-

Table 7
Fama–MacBeth regressions controlling for limits of arbitrage. We run the value-weighted Fama and MacBeth (1973) regressions, using firm size in month t as the weight. We run the cross-sectional regressions of firm excess returns in month $t+1$ ($EXRET_{i,t+1}$) on idiosyncratic volatility of month $t(IVOL^{ran}_{i,t})$, together with control variables and the interaction terms of limits-of-arbitrage index dummies and $IVOL^{ran}_{i,t}$. We then calculate the time series of regression coefficients and test whether the average coefficients are significantly different from zero. We use the scaled monthly decile rank for explanatory variables with the superscript “ran”. Specifically, we rank the values of $IVOL$, $EXRET$ $lnMV$, $lnBM$, $TURN$, and $MAX5$ of each firm into deciles in every month. All decile ranks are then scaled to take the value ranging between −0.5 and 0.5. The dummy variable $LOW_{i,t}/MEDIUM_{i,t}/HIGH_{i,t}$ is assigned one if stock i belongs to the bottom tercile/middle tercile/top tercile based on limits-of-arbitrage index in month t. The last row reports the average adjusted R-squares of the cross-sectional regressions. The sample period is from January 2002 to December 2012. Newey and West (1987) t-statistics with 4 lags are reported in parentheses; *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
$IVOL^{ran}_{i,t}$	−1.08***		−0.69
	(−2.87)		(−1.65)
$IVOL^{ran}_{i,t} * LOW_{i,t}$		−0.69	
		(−1.65)	
$IVOL^{ran}_{i,t} * MEDIUM_{i,t}$		−1.57***	−0.88**
		(−3.55)	(−2.29)
$IVOL^{ran}_{i,t} * HIGH_{i,t}$		−2.07***	−1.37***
		(−4.90)	(−2.82)
$EXRET^{ran}_{i,t}$	−0.99**	−0.96**	−0.96**
	(−2.06)	(−1.99)	(−1.99)
$lnMV^{ran}_{i,t}$	−0.88	−0.84	−0.84
	(−1.24)	(−1.19)	(−1.19)
$lnBM^{ran}_{i,t}$	0.36	0.37	0.37
	(0.97)	(0.99)	(0.99)
$TURN^{ran}_{i,t}$	−0.70*	−0.72*	−0.72*
	(−1.76)	(−1.79)	(−1.79)
$MAX5^{ran}_{i,t}$	0.17	0.12	0.12
	(0.32)	(0.24)	(0.24)
R^2	14.9%	15.3%	15.3%

[7] We also conduct the equally-weighted Fama–MacBeth regressions for robustness check and obtain similar results.

fect, value effect, turnover, and maximum daily returns. Using the decile coding −0.5 to 0.5, the coefficient estimate of −1.08 suggests that the trading strategy of buying the lowest IVOL and selling the highest IVOL stocks yields a monthly risk-adjusted return of 1.08%.

The second and third regressions include the interaction terms of IVOL and dummy variables based on the limits-of-arbitrage index. In the second specification, we include all the three interactive variables ($IVOL^{ran}_{i,t} * LOW_{i,t}$, $IVOL^{ran}_{i,t} * MEDIUM_{i,t}$, and $IVOL^{ran}_{i,t} * HIGH_{i,t}$) to study the IVOL return premium in three limits-of-arbitrage sorted portfolios (low, medium, and high), respectively. The coefficient estimate of $IVOL^{ran}_{i,t} * LOW_{i,t}$ is −0.69, with *t*-statistic of −1.65. The low significance of this coefficient is consistent with our previous observation that IVOL return premium is weak in low limits-of-arbitrage stocks. The coefficient of $IVOL^{ran}_{i,t} * MEDIUM_{i,t}$ is −1.57 (*t*-statistic = −3.55) and the coefficient of $IVOL^{ran}_{i,t} * HIGH_{i,t}$ is −2.07 (*t*-statistic = −4.90), both significant at 1% level. Our regression estimates imply that the trading strategy of buying the lowest IVOL and selling the highest IVOL stocks yields a monthly risk-adjusted return of 0.69%, 1.57%, and 2.07% for low, medium, and high limits-of-arbitrage tercile, respectively. The magnitude of IVOL return premiums in three subsamples is comparable to the sorting results in Table 3.

In the third specification, we use low limits-to-arbitrage tercile portfolio as the baseline and test whether there is any difference of IVOL return premium in medium and high limits-of-arbitrage stocks. The coefficient of $IVOL^{ran}_{i,t} * MEDIUM_{i,t}$ is −0.88 (*t*-statistic = −2.29), which indicates that the difference of IVOL effect between low and medium limits-to-arbitrage stocks is significant at 5% level. The coefficient of $IVOL^{ran}_{i,t} * HIGH_{i,t}$ is even more negatively significant, with the value of −1.37 (*t*-statistic = −2.82), significant at 1% level. This observation is consistent with our previous finding that the negative IVOL effect becomes stronger in high limits-to-arbitrage stocks.

Overall, the empirical evidence in this section suggests that the negative return premium of idiosyncratic volatility is more significant in stocks with high limits of arbitrage than those with low limits of arbitrage.

4. Extended discussion

We examine whether the existing explanations from the related literature, such as the short-term return reversal (Huang et al., 2009), the lottery-like stock preference (Bali et al., 2011), and arbitrage asymmetry (Stambaugh et al., 2015), can be applied to what we have observed in the Chinese stock market.

4.1. Short-term return reversal

In this subsection, we discuss the short-term reversal explanation proposed by Huang et al. (2009). Huang et al. (2009) suggest that AHXZ's results are driven by monthly stock return reversals. After controlling for the previous-month return, the negative relation between average return and the lagged idiosyncratic volatility disappears. Fu (2009) also implies that AHXZ's findings are largely explained by the return reversal of a subset of small stocks with high idiosyncratic volatility. We discuss the possibility of short-term reversal explanation. We provide three layers of empirical evidence that suggest the short-term return reversal is unlikely to explain the IVOL negative premium observed in the Chinese stock market.

First, Huang et al. (2009) argue that if the IVOL negative premium is caused by the short-term return reversal, the return difference between the high and low idiosyncratic volatility portfolios should be less significant, or even insignificant, when portfolio returns are constructed by the equally-weighted (EW) method. For example, Huang et al. (2009) show that in the US market, the value-weighted (VW) return difference between the high and low IVOL portfolios is a significant −1.000% per month, while the EW monthly return difference is only −0.005% with a *t*-statistics of −0.01 (see their Table 3). However, we find a remarkably different picture in the Chinese stock market. Table 2 Panel B in our paper shows that the EW risk-adjusted return difference between the highest and lowest IVOL decile portfolios is −2.20% per month (with a *t*-statistics of −7.84). In other words, the IVOL premium obtained under the equally-weighted method is not only statistically significant, but also larger in economic magnitude than the value-weighted results, which is −1.40% per month.

Second, for the Fama–Macbeth regression reported in our Table 7, we have included the previous-month stock return variable as a control for the influence of short-term return reversal on the pricing of idiosyncratic volatility. We find a significantly negative coefficient on this lag return variable, which suggests that short-term reversal does exist in the Chinese stock market. More importantly, we want to highlight that after controlling for the short-term reversal effect, we still find a significantly negative coefficient on the firm idiosyncratic volatility variable in this return-prediction regression. This observation again is very different from what Huang et al. (2009) find in their regression (see their Table 2). In addition, our finding that the IVOL negative premium is more prominent in stocks with high limits of arbitrage than those with low limits of arbitrage remains robust after controlling for short-term return reversal.

Third, we construct a Chinese stock market short-term reversal factor (STREV) following the U.S. short-term reversal factor construction method provided at Kenneth French's website. [8] In Panel A of Table 8, we perform a finer risk adjustment by including a momentum factor (UMD) [9] and this short-term reversal factor (STREV). After controlling for the standard Fama–French three factors and these two additional factors, we are still able to obtain a significantly negative intercept as of −1.05% per month. This suggests that neither momentum nor short-term reversal can explain the IVOL negative premium in the Chinese stock market. Moreover, in Panel B of Table 8, we repeat the two-way portfolio sorting analysis based on limits of arbitrage and idiosyncratic volatility, and report the risk-adjusted portfolio returns under the five-factor model framework introduced above. Our previous result that the IVOL negative premium is stronger in high limits-of-arbitrage stocks retains after controlling for the short-term reversal factor.

4.2. Lottery-like stock payoff feature

In this subsection, we discuss the possibility of the IVOL negative premium to be explained by the lottery-type stocks preference as documented in Bali et al. (2011). Bali et al. (2011) construct a measure for stocks lottery-like payoffs, which is calculated as the maximum daily return or the average of five highest daily returns over the past month. They show a significantly negative relation between this maximum-return measure and expected stock returns, and it can explain the IVOL negative premium observed in the U.S. market. Following Bali et al. (2011), we use the average of the five highest daily returns in the previous month, *MAX5*, to proxy for stock lottery-like payoff feature in the Chinese market. We then discuss the influence of lottery-type stocks preference on

[8] STREV is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. More specifically, we follow exactly the same method provided by Kenneth French's website, that is, STREV = (Small Low + Big Low)/2 − (Small High + Big High)/2, and construct the short-term reversal factor in the Chinese stock market correspondingly.

[9] UMD is the return for the momentum factor, extracted from RESSET Financial Database, which is constructed by following the methodology provided by Kenneth French's website.

Table 8
Short-term reversal effect. In this table, we use time-series regressions and portfolio sorting method to examine the possibility of short-term return reversal explanation. We consider five risk factors include Fama–French three factors (RMRF, SMB, and HML), the momentum factor (UMD) from Carhart (1997), and the short-term reversal factor (STREV) following Kenneth French's website. The sample period is from January 2002 to December 2012; Newey and West (1987) robust *t*-statistics are reported in parentheses. Panel A presents the results of time-series regressions. The dependent variable is the monthly returns spread of quintile IVOL portfolio (long the highest IVOL quintile and short the lowest IVOL quintile). Adjusted *R*-squares are in the last row. In panel B, we form a two-way portfolio sorting by limits of arbitrage and idiosyncratic volatility. First, we categorize stocks into terciles based on their limits-of-arbitrage index in month *t*. The index is the average of six limits-of-arbitrage indicators, consisting of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details). Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility over month *t*, from the lowest (P1) to the highest (P5) idiosyncratic volatility. In month $t+1$, the risk-adjusted portfolio returns under the five-factor model of each portfolio are reported (in percent). Newey and West (1987) *t*-statistics with 4 lags are reported in parentheses; *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

Panel A: one-way sorting controlling for short-term reversal factor

	(1)	(2)	(3)	(4)
Constant	−1.09***	−1.19***	−0.87**	−1.05***
	(−*2.82*)	(−*3.32*)	(−*2.13*)	(−*2.78*)
SMB_{t+1}	0.10	0.29*	0.15	0.31**
	(*0.71*)	(*1.95*)	(*1.02*)	(*1.98*)
HML_{t+1}	−0.56***	−0.50 ***	−0.58 ***	−0.52***
	(−*2.79*)	(−*2.74*)	(−*2.99*)	(−*2.86*)
$RMRF_{t+1}$	0.18***	0.19***	0.18***	0.19***
	(*4.30*)	(*4.27*)	(*4.23*)	(*4.24*)
UMD_{t+1}		0.32**		0.28**
		(*2.28*)		(*2.06*)
$STREV_{t+1}$			−0.21	−0.13
			(−*1.58*)	(−*1.00*)
R^2	23.4%	28.7%	25.3%	29.0%

Panel B: two-way sorting controlling for short-term reversal factor
Five-factor risk adjusted returns

	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted							
Low limits of arbitrage	0.05	0.07	0.27	0.00	−0.36	−0.41	(−*1.00*)
Medium limits of arbitrage	0.43	0.13	−0.16	−0.62	−1.15	−1.58	(−*4.48*)
High limits of arbitrage	1.00	0.58	0.27	−0.35	−1.27	−2.28	(−*8.24*)
High–low						−1.87	(−*4.34*)
Equally-weighted							
Low limits of arbitrage	0.17	0.02	−0.06	−0.42	−0.81	−0.98	(−*3.42*)
Medium limits of arbitrage	0.63	0.21	−0.01	−0.57	−1.45	−2.08	(−*7.49*)
High limits of arbitrage	1.10	0.64	0.36	−0.28	−1.19	−2.29	(−*8.57*)
High–low						−1.31	(−*4.13*)

the pricing of idiosyncratic volatility from three following perspectives.

(4.2.a) We employ two-way dependent portfolio sorting method based on IVOL and *MAX5* for the estimation of IVOL premium. In the first step, we categorize stocks into ten groups based on its *MAX5* measure in the previous month. In the second step, within each *MAX5* group, we further sort stocks into ten IVOL portfolios. Then, the returns of high (D10) and low (D1) idiosyncratic volatility decile portfolios are calculated as the simple average returns of the highest and lowest IVOL sub-portfolios across ten *MAX5* groups. [10] The IVOL premium is estimated as the return difference between these two extreme idiosyncratic volatility portfolios, that is, D10–D1. The results obtained from this two-way dependent portfolio sorting procedure, as well as the original one-way sorted portfolio returns, are presented in Panel A of Table 9. The left half of Panel A (one-way sorted result) is exactly the same as Table 2 Panel B. The right half of Panel A (two-way sorted result) shows that, after controlling for the *MAX5* effect, the IVOL premium is still significantly negative, although its magnitude decreases modestly. For example, the risk-adjusted IVOL premium is −1.35% (−0.90%) per month, with its *t*-statistics being −4.70 (−3.00), for the equally-weighted (value-weighted) method.

In Panel B of Table 9, we repeat the two-way dependent portfolio sorting analysis in a similar way, except that we sort out the IVOL stock groups first, and then within each IVOL group, produce the *MAX5* stock sub-portfolios. In other words, in this panel, we want to report the relative returns based on stock's *MAX5* measure, controlling the IVOL effect. The left half of Panel B (one-way sorted result) shows that the stocks with high *MAX5* measure significantly underperform those with low *MAX5* measure, which is consistent with Bali et al. (2011). However, the right half of Panel B (two-way sorted result) shows that, once controlling for the IVOL effect, the return differences between high and low *MAX5* stock portfolios are no longer significant for both the equally-weighted and value-weighted methods.

In general, Table 9 implies that the pricing effect of idiosyncratic volatility dominates the pricing effect of stock lottery-like payoff features (e.g., *MAX5*) in the Chinese stock market.

(4.2.b) We examine whether our previous finding that the IVOL premium is more negative in high limits-of-arbitrage stocks still holds after controlling for the effect of the preference for lottery-type stocks. To answer this question, we adopt a three-way portfolio sorting method based on limits-of-arbitrage index, IVOL, and *MAX5*. In the first step, we sort stocks into terciles based on their limits-of-arbitrage index. In the second step, within each limits-of-arbitrage tercile, we conduct a two-way dependent portfolio sorting based on IVOL and *MAX5* in a similar way as described in (4.2.a) above.

Therefore, in Panel A of Table 10, within each limits-of-arbitrage tercile, we report the return difference between the high and

[10] This procedure follows the method used in Fama and French (1993), who take the difference of the simple averages of the two high book-to-market portfolio returns and of the two low book-to-market portfolio returns across large and small stocks to construct the value factor (HML), with the size effect controlled.

Table 9
Portfolio sorting by idiosyncratic volatility and maximum daily return. We employ two-way dependent portfolio sorting method based on IVOL and *MAX5* for the estimation of IVOL premium. Following Bali et al. (2011), we use the average of five highest daily returns in the previous month, *MAX5*, to proxy for stock lottery-like payoff feature. In the first step, we categorize stocks into ten groups based on its *MAX5* measure in the previous month. In the second step, within each *MAX5* group, we further sort stocks into ten IVOL portfolios. Then, the returns of high (D10) and low (D1) idiosyncratic volatility decile portfolios are calculated as the simple average returns of the highest and lowest IVOL sub-portfolios across ten *MAX5* groups. The IVOL premium is estimated as the return difference between these two extreme idiosyncratic volatility portfolios (D10–D1). The results obtained from this two-way dependent portfolio sorting procedure, as well as the original one-way sorted portfolio returns, are presented in Panel A. In Panel B, we repeat the two-way dependent portfolio sorting analysis in a similar way, except that we sort out the IVOL stock groups first, and then within each IVOL group, produce the *MAX5* stock sub-portfolios. The monthly equally-weighted/value-weighted average raw returns and Fama and French (1993) three-factor risk adjusted returns of each portfolio are reported (in percent). The sample period is from January 2002 to December 2012; *t*-statistics are in parentheses.

Panel A: sorting by IVOL

	One-way sorting by IVOL					Two-way sorting by ivol after controlling for *MAX5*			
	Equally-weighted		Value-weighted			Equally-weighted		Value-weighted	
	Raw returns	Risk adjusted returns	Raw returns	Risk adjusted returns		Raw returns	Risk adjusted returns	Raw returns	Risk adjusted returns
D1	2.06	0.62	1.32	0.21	D1	2.12	0.84	1.51	0.43
D2	2.05	0.60	1.37	0.23	D1	1.85	0.58	1.47	0.41
D3	1.89	0.39	1.17	0.01	D3	1.69	0.42	1.60	0.51
D4	1.81	0.36	1.38	0.23	D4	1.54	0.32	1.31	0.26
D5	1.73	0.24	1.53	0.34	D5	1.41	0.17	1.31	0.27
D6	1.58	0.15	1.34	0.22	D6	1.35	0.14	1.10	0.12
D7	1.41	−0.06	1.00	−0.13	D7	1.34	0.11	1.16	0.15
D8	0.97	−0.50	0.77	−0.41	D8	1.08	−0.14	0.94	−0.08
D9	0.69	−0.73	0.51	−0.68	D9	0.97	−0.27	0.80	−0.23
D10	−0.16	−1.58	−0.01	−1.19	D10	0.68	−0.51	0.54	−0.47
D10–D1	−2.21	−2.20	−1.32	−1.40	D10–D1	−1.44	−1.35	−0.97	−0.90
t-stat	(*−7.51*)	(*−7.84*)	(*−2.77*)	(*−3.37*)	*t-stat*	(*−4.77*)	(*−4.70*)	(*−2.92*)	(*−3.00*)

Panel B: sorting by *MAX5*

	One-way sorting by *MAX5*					Two-way sorting by *MAX5* after controlling for IVOL			
	Equally-weighted		Value-weighted			Equally-weighted		Value-weighted	
	Raw returns	Risk adjusted returns	Raw returns	Risk adjusted returns		Raw returns	Risk adjusted returns	Raw returns	Risk adjusted returns
D1	1.63	0.33	1.02	0.03	D1	1.28	0.19	0.88	0.00
D2	1.98	0.55	1.63	0.51	D1	1.50	0.30	1.36	0.37
D3	2.05	0.56	1.50	0.31	D3	1.41	0.18	1.26	0.24
D4	1.93	0.46	1.54	0.35	D4	1.52	0.26	1.19	0.13
D5	1.55	0.05	1.07	−0.17	D5	1.49	0.23	1.28	0.23
D6	1.61	0.10	1.48	0.28	D6	1.40	0.15	1.34	0.29
D7	1.39	−0.08	1.21	0.00	D7	1.31	0.04	1.11	0.00
D8	1.19	−0.30	1.20	0.00	D8	1.32	0.02	1.10	0.00
D9	0.75	−0.70	0.65	−0.51	D9	1.35	0.09	1.17	0.11
D10	0.04	−1.37	0.06	−1.13	D10	1.44	0.21	1.05	−0.01
D10–D1	−1.59	−1.70	−0.95	−1.16	D10–D1	0.16	0.03	0.17	0.00
t-stat	(*−4.59*)	(*−5.27*)	(*−1.93*)	(*−2.66*)	*t-stat*	(*0.46*)	(*0.08*)	(*0.41*)	(*−0.01*)

low idiosyncratic volatility portfolios after controlling for *MAX5* measure. Similar to our original results, even after controlling for the lottery-type stock preference, we still find that the idiosyncratic volatility premium is stronger among high limits-of-arbitrage stocks, and it becomes much weaker, or even insignificant, in stocks with low limits of arbitrage. The difference-of-difference test suggests that the IVOL premium obtained in high and low limits-of-arbitrage stocks are significantly different from each other. As a contrast, in Panel B of Table 10, although we find some indication that the underperformance of high *MAX5* stocks is a little bit stronger in the high limits-of-arbitrage tercile, the statistics significance of this result is low.

(4.2.c) To ensure the robustness of our results, besides the portfolio sorting approach, we also adopt the Fama and MacBeth (1973) regression method. The regression coefficients are presented in the appendix Table A5. The first and second columns in this table are univariate regressions, in which next-month stock return is regressed on IVOL and *MAX5*. The regression results suggest that both high IVOL and high *MAX5* measures can lead to lower return in the next month in the univariate regression setting. However, when these two measures are included in the regression at the same time, as shown in the third column, the IVOL coefficient estimate remains significantly negative, while the *MAX5* coefficient estimate becomes indiscernible from zero. This observation suggests that, when put together, the pricing effect of lottery-like stock payoff features is subsumed by the pricing effect of idiosyncratic volatility. We repeat this analysis in column 4–6, with additional control variables added into the regressions, and find a similar result that the pricing of idiosyncratic volatility is more important than the pricing of lottery-like stock payoff features.

Taken together, the empirical results presented in this subsection suggest that, although there are some indications that lottery-like stock payoff features are negatively priced in the Chinese stock market, the pricing of this lottery-type payoff feature is dominated by the pricing of idiosyncratic volatility. Moreover, we find that the preference of lottery-type stocks has limited explanatory power for our main findings about the IVOL negative premium and its interaction with limits of arbitrage.

4.3. Arbitrage asymmetry

Stambaugh et al. (2015) suggest that the negative relation between IVOL and subsequent returns can be explained by arbitrage asymmetry caused by short-sell constraint. They find a modest positive IVOL premium in underpriced stocks, but a much stronger negative IVOL premium in overpriced stocks. As a result, the unconditional IVOL premium becomes negative as an average of these

Table 10

Portfolio sorting by limits of arbitrage, IVOL and *MAX5*. We adopt a three-way portfolio sorting method based on limits-of-arbitrage index, IVOL, and *MAX5*. Following Bali et al. (2011), we use the average of five highest daily returns in the previous month, *MAX5*, to proxy for stock lottery-like payoff feature. In the first step, we sort stocks into terciles based on their limits-of-arbitrage index. In the second step, within each limits-of-arbitrage tercile, we conduct a two-way dependent portfolio sorting based on IVOL and *MAX5*. Specifically, we categorize stocks into five groups based on its *MAX5* measure in the previous month. Within each *MAX5* group, we further sort stocks into five IVOL portfolios. Then, the returns of high (P5) and low (P1) idiosyncratic volatility portfolios are calculated as the simple average returns of the highest and lowest IVOL sub-portfolios across five *MAX5* groups. The IVOL premium is estimated as the return difference between these two extreme idiosyncratic volatility portfolios (P5–P1). The results obtained from this three-way portfolio sorting procedure are presented in Panel A. In Panel B, we repeat the three-way portfolio sorting analysis in a similar way, except that we first sort out the IVOL stock groups among each limits-of-arbitrage tercile, and then within each IVOL group, produce the *MAX5* stock sub-portfolios. The monthly equally-weighted/value-weighted average raw returns and Fama and French (1993) three-factor risk adjusted returns of each portfolio are reported (in percent). The sample period is from January 2002 to December 2012; *t*-statistics are in parentheses.

Panel A: three-way sorting by limits of arbitrage and IVOL after controlling for *MAX5*	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.26	1.43	1.15	1.17	0.80	−0.46	(*−1.41*)
Medium limits of arbitrage	1.71	1.39	1.13	1.05	0.48	−1.22	(*−4.26*)
High limits of arbitrage	2.39	1.82	1.51	1.45	0.82	−1.57	(*−5.63*)
High–low						−1.11	(*−2.99*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.16	0.30	0.07	0.13	−0.21	−0.36	(*−1.19*)
Medium limits of arbitrage	0.27	−0.02	−0.23	−0.35	−0.83	−1.10	(*−3.91*)
High limits of arbitrage	0.72	0.23	−0.06	−0.14	−0.70	−1.43	(*−5.19*)
High–low						−1.07	(*−2.89*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	1.58	1.36	1.14	1.03	0.69	−0.89	(*−3.46*)
Medium limits of arbitrage	2.01	1.51	1.31	1.16	0.61	−1.40	(*−5.84*)
High limits of arbitrage	2.46	2.00	1.70	1.54	1.00	−1.47	(*−5.51*)
High–low						−0.58	(*−2.06*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.26	0.06	−0.13	−0.19	−0.50	−0.75	(*−3.15*)
Medium limits of arbitrage	0.52	0.02	−0.15	−0.30	−0.80	−1.32	(*−5.51*)
High limits of arbitrage	0.77	0.37	0.08	−0.11	−0.60	−1.37	(*−5.18*)
High–low						−0.62	(*−2.22*)

Panel B: three-way sorting by limits of arbitrage and *MAX5* after controlling IVOL	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.18	1.33	1.14	1.10	1.06	−0.12	(*−0.30*)
Medium limits of arbitrage	1.18	1.29	1.16	1.19	1.02	−0.16	(*−0.45*)
High limits of arbitrage	1.75	1.82	1.45	1.57	1.41	−0.34	(*−1.35*)
High–low						−0.22	(*−0.51*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.25	0.24	0.00	0.02	−0.04	−0.29	(*−0.82*)
Medium limits of arbitrage	−0.12	−0.07	−0.24	−0.24	−0.41	−0.29	(*−0.89*)
High limits of arbitrage	0.22	0.21	−0.17	−0.02	−0.20	−0.42	(*−1.63*)
High–low						−0.13	(*−0.33*)
Equally-weighted raw returns							
Low limits of arbitrage	1.09	1.25	1.15	1.11	1.20	0.12	(*0.34*)
Medium limits of arbitrage	1.36	1.37	1.25	1.36	1.24	−0.11	(*−0.38*)
High limits of arbitrage	1.98	1.93	1.59	1.68	1.53	−0.45	(*−1.84*)
High–low						−0.57	(*−1.63*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	−0.01	0.00	−0.16	−0.21	−0.12	−0.11	(*−0.39*)
Medium limits of arbitrage	−0.02	−0.08	−0.23	−0.15	−0.24	−0.22	(*−0.76*)
High limits of arbitrage	0.38	0.28	−0.06	0.05	−0.13	−0.51	(*−2.04*)
High–low						−0.40	(*−1.30*)

two. In this section, we examine whether the relation between IVOL premium and stocks' overpricing/underpricing status holds true for the Chinese stock market, particularly for stocks with different levels of limits of arbitrage.

As a start, we construct an overpricing/underpricing measure by utilizing anomalies variables, following Stambaugh et al. (2015).[11]

There are two steps to construct this measure. First, we assign a decile rank which reflects the monthly sorting on each of the six anomaly variables. Decile 10 (decile 1) is assigned to the observations of an anomaly variable with the lowest (highest) average expected return. Next, we calculate a stock's overpricing/underpricing measure in that month as the arithmetic average of its ranks of each of the six anomalies. We label stocks with the measure in the higher (lower) half as the overpriced (underpriced) stocks.

We then perform a three-way portfolio sorting. We first sort stocks into terciles based on limits-of-arbitrage index, including low, medium, and high limits-of-arbitrage stocks. Mean-

[11] Stambaugh et al. (2015) employ 11 anomalies to construct the relative overpricing/underpricing measure. We use six of them, including accruals, net operating assets, profitability, return-on-equity, momentum, and equity issuance, due to data availability and the effectiveness of the anomalies in the Chinese stock market. We detail the six anomalies in the appendix Table A6.

Table 11
Portfolio sorting by limits of arbitrage, overpricing/underpricing measure, and idiosyncratic volatility. At the end of month t, we sort stocks into terciles by limits-of-arbitrage index, including low, medium, and high limits-of-arbitrage stocks. Meanwhile, stocks are sorted into two groups based on the overpricing/underpricing measure: underpriced stocks and overpriced stocks. The overpricing/underpricing measure is calculated as the arithmetic average rank of the six anomalies variables in month t. The six anomalies variables include accruals, net operating assets, profitability, return-on-equity, momentum and equity issuance (see appendix Table A6 for details). Within each independent sorting group, stocks are further sorted into quintiles by their idiosyncratic volatility over month t. For each three-way sorting portfolio, we tabulate 1-month-ahead value-weighted average raw returns in Panel A, and Fama and French (1993) three-factor risk adjusted returns in Panel B. The full sample period is from January 2002 to December 2012; t-statistics are in parentheses.

Panel A: raw returns

	Low limits of arbitrage		Medium limits of arbitrage		High limits of arbitrage	
	Underpriced	Overpriced	Underpriced	Overpriced	Underpriced	Overpriced
P1	1.13	1.33	1.84	1.82	2.44	2.54
P2	1.44	0.79	1.59	1.60	2.23	2.16
P3	1.63	0.90	1.68	1.18	1.92	1.74
P4	1.51	0.03	0.92	0.62	1.37	1.06
P5	0.88	0.04	0.26	−0.05	0.35	0.06
P5–P1	−0.26	−1.29	−1.58	−1.88	−2.09	−2.48
t-stat	*(−0.58)*	*(−2.75)*	*(−3.58)*	*(−4.70)*	*(−6.14)*	*(−8.43)*
Overpriced–underpriced		−1.04		−0.30		−0.39
t-stat		*(−2.20)*		*(−0.62)*		*(−1.21)*

Panel B: Fama–French three-factor risk adjusted returns

	Low limits of arbitrage		Medium limits of arbitrage		High limits of arbitrage	
	Underpriced	Overpriced	Underpriced	Overpriced	Underpriced	Overpriced
P1	0.17	0.16	0.57	0.23	0.87	0.84
P2	0.47	−0.59	0.33	−0.06	0.69	0.46
P3	0.67	−0.35	0.44	−0.37	0.46	0.04
P4	0.59	−1.26	−0.29	−0.94	−0.01	−0.61
P5	−0.09	−1.13	−0.88	−1.52	−1.05	−1.49
P5–P1	−0.26	−1.29	−1.45	−1.75	−1.91	−2.34
t-stat	*(−0.64)*	*(−2.75)*	*(−3.53)*	*(−4.55)*	*(−5.77)*	*(−8.29)*
Overpriced–Underpriced		−1.04		−0.30		−0.42
t-stat		*(−2.18)*		*(−0.61)*		*(−1.29)*

while, stocks are sorted into two groups based on their overpricing/underpricing measure. With these sorting combined, we have six independent-sorting groups. Within each group, stocks are further sorted into quintiles by their idiosyncratic volatility in month t. For these three-way-sorted portfolios, we tabulate 1-month-ahead value-weighted average raw returns and Fama and French (1993) three-factor risk adjusted returns in Table 11.

In Table 11, we report the return differences between the high and low IVOL stocks within each limits-of-arbitrage and overpricing/underpricing group. We then calculate the difference in IVOL premium between underpriced and overpriced stocks, and find the arbitrage asymmetry explanation proposed by Stambaugh et al. (2015) holds true for low limits-of-arbitrage stocks, but not for medium and high limits-of-arbitrage stocks, in the Chinese stock market.

In Panel A, within the low limits-of-arbitrage portfolio, the IVOL premium for underpriced stocks is insignificant (−0.26% per month with t-statistic = −0.58), while the IVOL premium for overpriced stocks is much larger in economic magnitude (−1.29% per month) and also statistically significant (t-statistic = −2.75). The difference between IVOL premium in overpriced and underpriced stocks is −1.04% per month (t-statistic = −2.20). Therefore, we conclude that for Chinese stocks with low limits of arbitrage, the relationship between the pricing of idiosyncratic volatility and stocks' overpricing/underpricing status is consistent with what Stambaugh et al. (2015) find in the U.S. equity market.

However, this pattern does not hold for stocks with high limits of arbitrage. In the high limits-of-arbitrage tercile, the IVOL raw return premium is −2.09% (t-statistic = −6.14) and −2.48% (t-statistic = −8.43) per month for underpriced and overpriced stocks, respectively. The difference between these two return premiums is not statistically significant. We also obtain similar results based on Fama–French three-factor model, that is, stocks with high IVOL deliver lower risk-adjusted returns for both underpriced and overpriced stocks within the high (and the medium) limits-of-arbitrage tercile portfolios.

We also conduct value-weighted Fama and MacBeth (1973) regressions to ensure the robustness of our empirical results here. Similar to the section above, we use the scaled monthly decile rank for explanatory variables with the superscript "*ran*". We introduce two new dummies – $UNDER_{i,t}$ and $OVER_{i,t}$ $UNDER_{i,t}(OVER_{i,t})$ is assigned one if the overpricing/underpricing measure of stock i belongs to its lower (higher) half in month t.

In the first specification of Table 12, the coefficient of $IVOL_{i,t}^{ran} * UNDER_{i,t}$ is −0.87 (t-statistic = −1.96), and the coefficient of $IVOL_{i,t}^{ran} * OVER_{i,t}$ is −1.60 (t-statistic = −3.89), which indicates that overpriced stocks make more contribution to the negative IVOL spreads than underpriced stocks. The second specifications consider both limits-of-arbitrage dummies and overpricing/underpricing dummies. Specifically, the coefficient of $IVOL_{i,t}^{ran} * LOW_{i,t} * UNDER_{i,t}$ is −0.50 (t-statistic = −1.03) and the coefficient of $IVOL_{i,t}^{ran} * LOW_{i,t} * OVER_{i,t}$ is −1.47 (t-statistic = −2.88), implying that, within low limits-of-arbitrage portfolio, the IVOL premium is stronger in overpriced stocks than in underpriced stocks. What we find so far is consistent with Stambaugh et al. (2015). However, the coefficient of $IVOL_{i,t}^{ran} * MEDIUM_{i,t} * UNDER_{i,t}$ is −1.61 (t-statistic = −3.29), and the coefficient of $IVOL_{i,t}^{ran} * MEDIUM_{i,t} * OVER_{i,t}$ is −1.76 (t-statistic = −3.44); the coefficient of $IVOL_{i,t}^{ran} * HIGH_{i,t} * UNDER_{i,t}$ is −2.09 (t-statistic = −4.02), and the coefficient of $IVOL_{i,t}^{ran} * HIGH_{i,t} * OVER_{i,t}$ is −2.14 (t-statistic = −5.32). Within medium and high limits-of-arbitrage portfolios, we find significant negative IVOL premium in both overpriced and underpriced stocks.

We conjecture that the reason about why there is no difference of IVOL premium between overpriced and underpriced stocks for stocks with high limits of arbitrage is that these stocks are in fact universally *overpriced*. In the appendix Table A7, we report the median of price-earnings ratios in Panel A, and the market-wide average price-earnings ratio, following the method of Huang and Wirjanto (2012), in Panel B. We consider the total sample pe-

Table 12
Fama–MacBeth regressions controlling for limits of arbitrage and overpricing/underpricing. We run the value-weighted Fama and MacBeth (1973) regressions, using the lagged firm size as the weight. We run the cross-sectional regressions of firm excess returns in month $t+1$ on the idiosyncratic volatility of month t ($IVOL^{ran}_{i,t}$) together with control variables and interaction terms. We then calculate the time series of regression coefficients and test whether the average coefficients are significantly different from zero. $UNDER_{i,t}$($OVER_{i,t}$) is assigned one if the overpricing/underpricing measure of stock i belongs to its lower (upper) half in month t. We use the scaled monthly decile rank for explanatory variables with the superscript "ran". $LOW_{i,t}$/$MEDIUM_{i,t}$/$HIGH_{i,t}$ is assigned one if the stock i belongs to the bottom tercile/middle tercile/top tercile based on limits-of-arbitrage index in month t. The last row reports the average adjusted *R*-squares of the cross-sectional regressions. The full sample period is from January 2002 to December 2012. Newey and West (1987) *t*-statistics with 4 lags are reported in parentheses. *; ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

	(1)	(2)
$IVOL^{ran}_{i,t} * UNDER_{i,t}$	−0.87*	
	(−*1.96*)	
$IVOL^{ran}_{i,t} * OVER_{i,t}$	−1.60***	
	(−*3.89*)	
$IVOL^{ran}_{i,t} * LOW_{i,t} * UNDER_{i,t}$		−0.50
		(−*1.03*)
$IVOL^{ran}_{i,t} * MEDIUM_{i,t} * UNDER_{i,t}$		−1.61***
		(−*3.29*)
$IVOL^{ran}_{i,t} * HIGH_{i,t} * UNDER_{i,t}$		−2.09***
		(−*4.02*)
$IVOL^{ran}_{i,t} * LOW_{i,t} * OVER_{i,t}$		−1.47***
		(−*2.88*)
$IVOL^{ran}_{i,t} * MEDIUM_{i,t} * OVER_{i,t}$		−1.76***
		(−*3.44*)
$IVOL^{ran}_{i,t} * HIGH_{i,t} * OVER_{i,t}$		−2.14***
		(−*5.32*)
$EXRET^{ran}_{i,t}$	−0.99**	−0.96**
	(−*2.07*)	(−*2.00*)
$lnMV^{ran}_{i,t}$	−0.88	−0.83
	(−*1.24*)	(−*1.17*)
$lnBM^{ran}_{i,t}$	0.34	0.33
	(*0.89*)	(*0.89*)
$TURN^{ran}_{i,t}$	−0.69*	−0.69*
	(−*1.71*)	(−*1.73*)
$MAX5^{ran}_{i,t}$	0.20	0.18
	(*0.38*)	(*0.34*)
R^2	15.3%	16.0%

riod (2002–2012), and also two sub-samples periods (2002–2007 and 2008–2012). The medians of P/E ratios are always higher in overpriced stocks than in underpriced stocks in a given limits-of-arbitrage category, suggesting our overpricing/underpricing measure works as expected. More importantly, we find that the P/E ratios are higher in stocks with high limits of arbitrage. For example, high limits-of-arbitrage and underpriced stocks have a median P/E ratio of 50.9, which is higher than that of 43.0 for low limits-of-arbitrage and overpriced stocks. As we can observe, the P/E ratios within high limits-of-arbitrage portfolio are quite high for stocks with both the "underpriced" and "overpriced" labels.

In fact, we observe that stocks listed in the Chinese market tend to have high valuation levels – the overall median P/E ratio is 50.7, much higher than the typical valuation levels in developed markets (see Chan et al., 2001). Such high valuation levels could be possibly attributed to the additional trading constraints in the Chinese stock market as we introduced above. Regulators often introduce trading constraint policies in the name of investor protection. But, as our study suggests, the additional trading constraints can lead to higher limits of arbitrage, undermine the efficiency of capital markets, and hurt investors' social welfare eventually.

Overall, the empirical analysis conducted in this section suggests that the existing explanations proposed by previous studies about the IVOL negative premium, such as short-term return reversal, the lottery-like stock preference, and arbitrage asymmetry, cannot fully explain our findings. It highlights the importance of studying how idiosyncratic volatility is priced in non-U.S. market. Most of the extant explanations of IVOL premium come from studies based on the U.S. market. We should not take for granted that their conclusion can always be applied to non-U.S. market without caution.

Although we do not offer a theory that can explain all aspects of the IVOL puzzle in this paper itself, our findings about the pricing of idiosyncratic volatility and how it is related with limits of arbitrage in an important non-U.S. market do shed more light for financial economists who want to develop better theoretical frameworks that can explain the IVOL premium in the future. A persuasive theory should be able to explain how idiosyncratic volatility is priced in both developed market (e.g., U.S.) and emerging market (e.g., China), as well as the role of limits of arbitrage in this pricing mechanism.

5. Conclusion

In this paper, we study how the pricing of idiosyncratic volatility is influenced by limits of arbitrage. We find a highly significant negative return premium for stocks with high idiosyncratic volatility in the Chinese stock market. More importantly, this IVOL negative premium is much stronger in stocks with high limits of arbitrage. We construct a comprehensive limits-of-arbitrage index using both unique trading constraints in the Chinese stock market and other limits-of-arbitrage measures that are commonly used in the literature. We find that the value-weighted risk-adjusted return difference between high and low idiosyncratic volatility stocks in the low limits-of-arbitrage portfolio is an insignificant −0.47% per month. As a sharp contrast, this IVOL return premium is amplified to −2.18% per month, being significant at 1% significance level.

Our empirical finding suggests that the IVOL premium can be interpreted as a symptom of market inefficiency. The IVOL negative premium becomes more prominent in stocks with high limits of arbitrage, as high limits of arbitrage increase the possibility and magnitude of market mispricing opportunity. To ensure the robustness of our results, we employ alternative definitions of the limits-of-arbitrage index, and confirm that our main finding that the IVOL negative premium is stronger in high limits-of-arbitrage stocks always holds.

We also examine whether the existing explanations about the IVOL premium can be applied to the Chinese stock market. Our analysis shows that the pricing of idiosyncratic volatility is unaffected by controlling the short-term return reversal and the lottery-type stock preference effect. The arbitrage asymmetry theory cannot fully explain our main findings either, particularly for high limits-of-arbitrage stocks. Therefore, our study suggests that when financial economists develop theoretical framework to explain the IVOL premium in the future, it should be able to be applied to both developed and emerging markets, and also accommodate the role of limits of arbitrage in the pricing of idiosyncratic volatility.

For policy implication, various trading constraints are often introduced in emerging markets in the name of investors' protection. However, our study shows that these trading constraints can actually lead to additional limits of arbitrage on the market. As a result, high idiosyncratic-volatility stocks, which are more likely to be held by individual investors, can get more overvalued and followed by lower subsequent returns. Therefore, to truly better protect individual investors, regulators should consider relaxing unnecessary trading constraints so that the securities on the market can priced in a more efficient manner.

Table A1
Description of individual components of limits-of-arbitrage index.

Indicator	Description
$LALIMIT_{i,t}$	In the Chinese stock market, there has been a 10% limit of daily price up or down for regular stocks and a 5% limit for stocks under special treatment since December 1996. Stocks hitting the price limit are more likely to face higher limits of arbitrage. $LALIMIT_{i,t}$ is assigned the value of one for stock i if it reaches at daily price limit for at least once in month t. The calculation period is from January 2002 to December 2012
$LAMTSS_{i,t}$	In the Chinese stock market, the margin trading and short selling (MTSS) policy, started from March 2010, is a pilot program which allows investors to borrow money to buy securities or to short sell via margin transactions. We expect that the stocks not included in MTSS are exposed to higher limits of arbitrage. $LAMTSS_{i,t}$ is assigned the value of one if stock i is excluded from this program in month t. The calculation period is from December 2011 to December 2012
$LACSI_{i,t}$	The CSI 300 future, listed on April 2010, is the only tradable index future in the Chinese stock market. We expect, for stocks that are not included the index, arbitrageurs will face a higher degree of limits of arbitrage. $LACSI_{i,t}$ is assigned the value of one if stock i does not belong to the CSI 300. The calculation period is from April 2010 to December 2012
$LAAMIHUD_{i,t}$	Stocks with higher illiquidity are more likely to have higher limits of arbitrage. We take log of the Amihud (2002) illiquidity measure and calculate the median in each month. $LAAMIHUD_{i,t}$ is assigned the value of one if stock i has a value larger than the cross-sectional median in month t. The calculation period is from January 2002 to December 2012
$LAVOL_{i,t}$	Stocks that experience lower trading volume are more likely to be associated with higher limits of arbitrage. $VOLUME_{i,t}$ is the average monthly volume over the past six months. $LAVOL_{i,t}$ is assigned the value of one if stock i's volume is less than or equal to the cross-sectional median in month t. The calculation period is from January 2002 to December 2012
$LACOV_{i,t}$	Stocks with less analyst coverage may have higher limits of arbitrage. $COV_{i,t}$ is the number of analysts covering firm i in month t. $LACOV_{i,t}$ is assigned the value of one if stock i's number of following analyst is less than or equal to the cross-sectional median in month t. The calculation period is from January 2005 to December 2012

Table A2
The distribution of limits-of-arbitrage index. The table reports the time series average of cross-sectional distribution of limits-of-arbitrage index estimated in each month following Fama–Macbeth two-step approach. In the first step, we estimate the cross-sectional distribution of limits-of-arbitrage index for each month. Then, in the second step, we calculate the time-series average of distributions obtained in the first step. The limits-of-arbitrage index is the average of six limits-of-arbitrage indicators, consisting of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details). Each of six indicators is assigned the value of one when high limits of arbitrage is recognized. The sample period is from January 2002 to December 2012.

Limits-of-arbitrage index	Number	Percentage
[0, 0.2)	315	20.8
[0.2, 0.4)	275	18.2
[0.4, 0.6)	243	16.0
[0.6, 0.8)	408	27.0
[0.8, 1]	271	17.9
Total	1512	100.0

Table A3
Correlations of individual components of limits-of-arbitrage index. The table reports the estimates of Pearson correlations among six individual limits-of-arbitrage indicators following Fama–Macbeth two-step approach. In the first step, we estimate the cross-sectional correlations among six individual limits-of-arbitrage indicators for each month. Then, in the second step, we calculate the time-series average of cross-sectional correlations obtained in the first step. $LALIMIT_{i,t}$ is assigned the value of one for stock i if it reaches at daily price limit for at least once in month t. $LAMTSS_{i,t}$ is assigned the value of one if stock i is excluded from this program in month t. $LACSI_{i,t}$ is assigned the value of one if stock i does not belong to the CSI 300. $LAAMIHUD_{i,t}$ is assigned the value of one if stock i has a value larger than the cross-sectional median in month t. $LAVOL_{i,t}$ is assigned the value of one if stock i's volume is less than or equal to the cross-sectional median in month t. $LACOV_{i,t}$ is assigned the value of one if stock i's number of following analyst is less than or equal to the cross-sectional median in month t. The full sample period is from January 2002 to December 2012.

	LALIMIT	LAMTSS	LACSI	LAAMIHUD	LACOV	LAVOL
LALIMIT	1.00	0.10	0.11	0.07	0.18	0.06
LAMTSS		1.00	0.76	0.35	0.24	0.35
LACSI			1.00	0.39	0.34	0.41
LAAMIHUD				1.00	0.30	0.68
LACOV					1.00	0.30
LAVOL						1.00

Note: All the correlations are significant at 5% significance level.

Appendix

See appendix Tables A1–A7.

Table A4
Portfolio sorting by limits of arbitrage and idiosyncratic volatility (by the index consisting of two limits-of-arbitrage indicators). We form a two-way portfolio sorting by limits of arbitrage and idiosyncratic volatility. First, we categorize stocks into terciles based on their limits-of-arbitrage index in month *t*. The index is the average of two limits-of-arbitrage indicators. In each panel, we choose two out of total six limits-of-arbitrage indicators. The six indicators consist of price-limit-hitting, the availability of margin trading and short-selling, the availability of index future, illiquidity, trading volume, and analyst coverage (see appendix Table A1 for details). Second, within each tercile, we further sort stocks into quintiles by their idiosyncratic volatility over month *t*, from the lowest (P1) to the highest (P5) idiosyncratic volatility. In month $t+1$, the average raw returns and Fama and French (1993) three-factor risk adjusted returns of each portfolio are reported (in percent). The sample period is from January 2002 to December 2012; *t*-statistics are in parentheses.

Panel A: index consisting of price-limit-hitting and trading volume	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.31	1.46	1.44	1.23	0.71	−0.60	(−1.49)
Medium limits of arbitrage	1.12	1.03	1.40	0.93	0.14	−0.98	(−2.14)
High limits of arbitrage	2.17	1.62	1.34	0.66	0.14	−2.03	(−5.84)
High–low						−1.43	(−3.35)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.23	0.43	0.38	0.19	−0.32	−0.55	(−1.53)
Medium limits of arbitrage	−0.15	−0.27	0.18	−0.32	−1.06	−0.91	(−2.31)
High limits of arbitrage	0.65	0.23	−0.07	−0.73	−1.26	−1.90	(−5.56)
High–low						−1.35	(−3.26)
Equally-weighted raw returns							
Low limits of arbitrage	1.68	1.71	1.48	1.15	0.50	−1.18	(−4.21)
Medium limits of arbitrage	2.13	1.84	1.65	1.11	0.22	−1.91	(−6.76)
High limits of arbitrage	2.51	2.17	1.80	1.04	0.05	−2.46	(−9.19)
High–low						−1.29	(−4.68)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.37	0.37	0.13	−0.14	−0.79	−1.16	(−4.35)
Medium limits of arbitrage	0.60	0.34	0.18	−0.38	−1.16	−1.76	(−7.18)
High limits of arbitrage	0.92	0.58	0.23	−0.53	−1.45	−2.37	(−8.96)
High–low						−1.21	(−4.41)

Panel B: index consisting of the availability of margin trading and short-selling and analyst coverage	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.62	1.89	2.65	1.97	1.39	−0.23	(−0.39)
Medium limits of arbitrage	1.69	1.85	1.78	1.68	0.91	−0.78	(−1.56)
High limits of arbitrage	3.10	2.30	2.42	1.62	0.78	−2.32	(−5.86)
High–low						−2.09	(−4.44)
Value-weighted risk adjusted returns s							
Low limits of arbitrage	−0.04	0.14	0.92	0.26	−0.57	−0.53	(−0.97)
Medium limits of arbitrage	−0.05	−0.23	−0.37	−0.47	−1.21	−1.15	(−2.47)
High limits of arbitrage	0.52	−0.37	−0.32	−1.04	−1.91	−2.42	(−6.15)
High–low						−1.89	(−4.03)
Equally-weighted raw returns							
Low limits of arbitrage	2.50	2.57	2.48	2.21	1.54	−0.96	(−2.64)
Medium limits of arbitrage	2.99	2.82	2.65	2.09	0.97	−2.02	(−6.05)
High limits of arbitrage	3.68	3.13	2.70	2.15	0.93	−2.76	(−9.07)
High–low						−1.80	(−5.13)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.29	0.30	0.21	−0.02	−0.75	−1.04	(−2.99)
Medium limits of arbitrage	0.51	0.22	0.04	−0.55	−1.58	−2.09	(−6.55)
High limits of arbitrage	0.93	0.26	−0.18	−0.71	−1.84	−2.76	(−9.07)
High–low						−1.73	(−4.83)

Table A4
(continued)

Panel C: index consisting of the availability of index future and illiquidity	P1	P2	P3	P4	P5	P5–P1	*t-stat*
Value-weighted raw returns							
Low limits of arbitrage	1.18	1.35	1.58	0.76	0.25	−0.93	(*−2.00*)
Medium limits of arbitrage	1.38	1.20	1.15	0.93	0.31	−1.07	(*−3.13*)
High limits of arbitrage	2.37	2.01	1.90	1.48	0.33	−2.04	(*−7.81*)
High–low						−1.12	(*−2.51*)
Value-weighted risk adjusted returns							
Low limits of arbitrage	0.10	0.27	0.54	−0.31	−0.89	−0.98	(*−2.37*)
Medium limits of arbitrage	0.27	0.00	−0.07	−0.27	−0.92	−1.19	(*−3.67*)
High limits of arbitrage	0.94	0.56	0.48	0.08	−1.07	−2.00	(*−7.65*)
High–low						−1.02	(*−2.45*)
Equally-weighted raw returns							
Low limits of arbitrage	1.43	1.48	1.39	0.69	−0.03	−1.46	(*−4.57*)
Medium limits of arbitrage	2.23	1.76	1.63	1.26	0.30	−1.93	(*−7.70*)
High limits of arbitrage	2.54	2.16	2.05	1.63	0.54	−2.00	(*−8.62*)
High–low						−0.54	(*−1.86*)
Equally-weighted risk adjusted returns							
Low limits of arbitrage	0.08	0.12	0.04	−0.65	−1.39	−1.47	(*−5.08*)
Medium limits of arbitrage	0.76	0.27	0.15	−0.24	−1.12	−1.88	(*−7.77*)
High limits of arbitrage	1.04	0.60	0.50	0.09	−0.97	−2.02	(*−8.69*)
High–low						−0.54	(*−1.96*)

Table A5
Fama–MacBeth regressions controlling for maximum daily return. Following Bali et al. (2011), we use the average of five highest daily returns in the previous month, *MAX5*, to proxy for stock lottery-like payoff feature. We employ the value-weighted Fama and MacBeth (1973) regressions, using firm size in month t as the weight. We run the cross-sectional regressions of firm excess returns in month $t+1$ ($EXRET_{i,t+1}$) on idiosyncratic volatility of month t($IVOL^{ran}_{i,t}$), the average of five highest daily returns in month t ($MAX5^{ran}_{i,t}$), with and without control variables. We then calculate the time series of regression coefficients and test whether the average coefficients are significantly different from zero. We use the scaled monthly decile rank for explanatory variables with the superscript "ran". The last row reports the average adjusted *R*-squares of the cross-sectional regressions. The sample period is from January 2002 to December 2012. Newey and West (1987) *t*-statistics with 4 lags are reported in parentheses; *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$IVOL^{ran}_{i,t}$	−0.90**		−1.07**	−0.98***		−1.08***
	(−2.04)		(−2.06)	(−2.81)		(−2.84)
$MAX5^{ran}_{i,t}$		−0.75*	0.05		−0.56	0.18
		(−1.83)	(0.10)		(−1.15)	(0.33)
$EXRET^{ran}_{i,t}$				−0.89**	−0.92*	−0.98**
				(−2.59)	(−1.91)	(−2.03)
$lnMV^{ran}_{i,t}$				−0.93	−0.86	−0.88
				(−1.27)	(−1.20)	(−1.24)
$lnBM^{ran}_{i,t}$				0.38	0.51	0.37
				(0.96)	(1.24)	(0.98)
$TURN^{ran}_{i,t}$				−0.62	−0.82**	−0.72*
				(−1.44)	(−2.02)	(−1.79)
R^2	3.1%	3.4%	5.3%	13.4%	14.0%	14.9%

Table A6
Description of individual components of overpricing/underpricing measure.

Indicator	Description
$ACCU_{i,t}$	Sloan (1996) finds that accruals are negatively related to future stock returns. Following Sloan (1996), accruals in fiscal year t are the change in noncash current assets less the change in current liabilities (exclusive of debt in current liabilities and income tax payable) and less depreciation, scaled by average total assets for previous two fiscal years
$NOA_{i,t}$	Hirshleifer et al. (2004) find that net operating assets are negatively related to future stock returns. Following Hirshleifer et al. (2004), we estimate the net operating assets as the difference between operating assets and operating liabilities on the balance sheet in fiscal year t, scaled by the total assets in fiscal year $t-1$
$GPP_{i,t}$	Novy-Marx (2013) shows that profitable firms generate significantly higher returns than unprofitable firms. We follow Novy-Marx (2013) and calculate the gross profitability premium as revenue minus cost of goods sold scaled by total assets in year t
$ROE_{i,t}$	Chen et al. (2011) show that firms with higher return-on-equity earn abnormally higher future average returns than that of firms with lower return-on-equity. We measure return-on-equity as one-quarter-lagged revenue over book equity
$MOM_{i,t}$	Jegadeesh and Titman (1993) document the momentum effect which predicts that stocks with higher (lower) past returns will have the higher (lower) future returns over the short and intermediate periods. We rank on 6/1/6 strategy. We roll over the portfolios formed on cumulative returns from month $t-6$ to month $t-1$ at the end of month t, skip on month, and hold it from month $t+1$ to month $t+6$
$CEI_{i,t}$	Daniel and Titman (2006) construct the composite equity issuance variable to measure the amount of equity the firm issues (or retires) in exchange for cash or services. They document that the composite equity issuance is significantly negatively related to future returns. We calculate a firm's composite equity issuance as the log change in market capitalization minus the log return in previous year

Table A7
Average price-earnings ratios by limits of arbitrage and overpricing/underpricing at the end of month t, we sort stocks into terciles by limits-of-arbitrage index, including low, medium, and high limits-of-arbitrage stocks. Meanwhile, stocks are sorted into two groups based on the overpricing/underpricing measure: underpriced stocks and overpriced stocks. Stocks within the upper (lower) half of measure are assigned as overpriced (underpriced) stocks in month t. The table reports the estimates of sample statistics following Fama–Macbeth two-step approach. In the first step, we estimate the cross-sectional statistics of each portfolio for each month. Then, in the second step, we calculate the time-series average of cross-sectional statistics obtained in the first step. We tabulate the median of price-earnings ratios in Panel A, and the market-wide average price-earnings ratios following the method of Huang and Wirjanto (2012) in Panel B. The full sample period is from January 2002 to December 2012. The first sub-period is from January 2002 to December 2007, and the second sub-period is from January 2008 to December 2012.

Panel A: median price-earnings ratios

	Full sample	Low limits of arbitrage		Medium limits of arbitrage		High limits of arbitrage	
		Underpriced	Overpriced	Underpriced	Overpriced	Underpriced	Overpriced
Full period: January 2002 to December 2012							
Average	50.7	26.7	43.0	40.2	61.6	50.9	82.1
First sub-period: January 2002 to December 2007							
Subsample average	50.4	24.2	40.0	34.6	69.4	49.8	92.2
Second sub-period: January 2008 to December 2012							
Subsample average	50.9	32.0	38.6	44.2	55.6	51.7	68.2

Panel B: market-wide price-earnings ratios

	Full sample	Low limits of arbitrage		Medium limits of arbitrage		High limits of arbitrage	
		Underpriced	Overpriced	Underpriced	Underpriced	Overpriced	Underpriced
Full period: January 2002 to December 2012							
Average	24.8	17.8	24.5	30.2	45.5	34.4	66.9
First sub-period: January 2002 to December 2007							
Subsample average	26.8	18.2	30.0	29.3	50.9	33.1	75.1
Second sub-period: January 2008 to December 2012							
Subsample average	21.7	17.5	20.1	31.9	39.5	38.5	55.1

References

Ali, A., Hwang, L., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. J. Financ. Econ. 69, 355–373.
Amihud, Yakov., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56.
Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 51, 259–299.
Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further U.S. evidence. J. Financ. Econ. 91, 1–23.
Asquith, Paul., Pathak, Parag., Ritter, Jay., 2005. Short interest, institutional ownership, and stock returns. J. Financ. Econ. 78, 243–276.
Bali, Turan G., Cakici, Nusret, Whitelaw, Robert F., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99, 427–446.
Bernard, V., Thomas, J., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. J. Acc. Econ. 13, 305–340.
Bessembinder, Hendrik, Zhang, Feng, 2013. Firm characteristics and long-run stock returns after corporate events. J. Financ. Econ. 109, 83–102.
Boyer, Brian, Mitton, Todd, Vorkink, Keith, 2010. Expected idiosyncratic skewness. Rev. Financ. Stud. 23, 169–202.
Cakici, N., Chan, K., Kudret, T., 2011, Cross-Sectional Stock Return Predictability in China, working paper.
Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.
Chan, Louis K.C., Lakonishok, Josef, Sougiannis, Theodore, 2001. The stock market valuation of research and development expenditures. J. Finance 56, 2431–24561.
Chen, Long, Novy-Marx, Robert, Zhang, Lu, 2011. An alternative three-factor model, Working paper.
Chordia, Tarun, Roll, Richard, Subrahmanyam, Avanidhar, 2008. Liquidity and market efficiency. J. Financ. Econ. 87, 249–268.
Daniel, Kent, Titman, Sheridan, 2006. Market reactions to tangible and intangible information. J. Finance 61, 1605–1643.
DeLong, Bradford, Shleifer, Andrei, Summers, Lawrence H., Waldmann, Robert, 1990. Noise trader risk in financial market. J. Polit. Econ. 90, 703–738.
Drew, M.E., Naughton, T., Veeraraghavan, M., 2004. Is idiosyncratic volatility priced?: evidence from the Shanghai stock exchange. Int. Rev. Financ. Anal. 13, 349–366.
Fama, Eugene F., French, Kenneth R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, Eugene F., MacBeth, James D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636.
Fu, Fangjian, 2009. Idiosyncratic risk and the cross-section of expected stock returns. J. Financ. Econ. 91, 24–37.
Han, Bing, Kumar, Alok, 2013. Speculative retail trading and asset prices. J. Financ. Quant. Anal. 48, 377–404.
Han, Yufeng, Lesmond, David, 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Rev. Financ. Stud. 24, 1590–1629.
Hirshleifer, David, Kewei, Hou, Teoh, Siew Hong, Yinglei, Zhang, 2004. Do investors overvalue firms with bloated balance sheets? J. Acc. Econ. 38, 297–331.
Hong, Harrison, Lim, Terence, Stein, Jeremy C., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. J. Finance 55, 265–295.
Huang, A.G., Wirjanto, T.S., 2012. Is China's P/E ratio too low? Examining the role of earnings volatility. Pac. Basin Finance J. 20, 41–61.
Huang, Wei, Qianqiu Liu, S., Rhee, Ghon, Zhang, Liang, 2009. Return reversals, idiosyncratic risk, and expected returns. Rev. Financ. Stud. 23, 147–168.
Jegadeesh, Narasimhan, Titman, Sheridan, 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48, 65–91.
Jones, Charles, Lamont, O., 2002. Short-sale constraints and stock returns. J. Financ. Econ. 66, 207–239.
Kim, Kenneth A., Ghon Rhee, S., 1997. Price limit performance: evidence from the Tokyo stock exchange. J. Finance 52, 885–901.
Lam, F.Y. Eric C., John Wei, K.C., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. J. Financ. Econ. 102, 127–149.
Liu, Y., Ping, Wang, 2013. Model selection and relationship between idiosyncratic volatility and expected stock returns: evidence from Chinese A-share market. In: Service Systems and Service Management (ICSSSM), 2013 10th International Conference.
Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. J. Acc. Econ. 42, 3–33.
Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. J. Financ. Econ. 78, 277–309.
Nartea, G.V., Wu, J., Liu, Z., 2013. Does idiosyncratic volatility matter in emerging markets? Evidence from China. J. Int. Financ. Mark. Inst. Money 27, 137–160.
Newey, Whitney K., West, Kenneth D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Novy-Marx, Robert, 2013. The other side of value: the gross profitability premium. J. Financ. Econ. 108, 1–28.
Sadka, Ronnie, Scherbina, Anna, 2007. Analyst disagreement, mispricing, and liquidity. J. Finance 62, 2367–2403.
Shleifer, Andrei, Vishny, Robert, 1997. The limits of arbitrage. J. Finance 52, 35–55.
Sloan, R.G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Acc. Rev. 71, 289–315.
Stambaugh, Robert F., Yu, Jianfeng, Yuan, Yu, 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. J. Finance 70, 1903–1948.