Research Article

Can Limits to Arbitrage Explain Stock Price Idiosyncratic Volatility Premium Puzzle in China’s A-Share Market?

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1.Introduction

The CAPM predicts that investors can only require compensation for bearing systematic risk because idiosyncratic risk is completely diversified away when the financial market is completely efficient. Prior studies show that investors in some markets cannot fully diversify their portfolios in practice [1]. Thus, idiosyncratic volatility (IV) will be expected to play a role in the risk-return relationship. One of the important tenets of modern portfolios theory is that systematic risk is the sole driver of returns, and thus idiosyncratic volatility cannot explain why returns of some stocks or portfolios are higher or lower than others [2]. Nevertheless, Merton [3] posited that investors cannot diversify their portfolios and require a positive risk premium for bearing idiosyncratic volatility. As a result, the relationship between idiosyncratic volatility and stock returns is positive.

However, the empirical asset pricing literature showed that the sign of the relationship between idiosyncratic volatility and stock returns is one of the most controversial topics. First, most of these empirical studies argue that idiosyncratic volatility is not priced [4]. Second, other literature concludes that stocks with higher idiosyncratic volatility command higher risk premium [5]. Third, many works argue that the relationship between idiosyncratic volatility and stock returns is negative [6], and this implies that the average return of stocks with low (high) idiosyncratic volatility is higher (lower) than others. The lack of consensus on the sign of the idiosyncratic volatility premium is called idiosyncratic volatility premium puzzle.

Some papers investigate the existence and causes of the idiosyncratic volatility premium puzzle, but it is also necessary for us to further investigate the causes of the idiosyncratic volatility premium puzzle in China’s A-share market. Gu et al. [7] use a sample containing all listed companies in Shanghai Stock Exchange and Shenzhen Stock Exchange, and the sample period spans from January 2002 to December 2012. They find that negative idiosyncratic volatility premium exists in China’s A-share market and this asset pricing effect is much stronger and more persistent in stocks with high limits of arbitrage. However, many new
regulation changes have taken place in China’s A-share market after 2012. One of the most important reforms is the enforcement of securities margin trading regulation. On March 30, 2010, securities margin trading regulation was enforced in some stocks in China’s A-share market. During the whole year 2010, the purchasing amount of margin trading accounts for about 0.16 percent of the total trading amount in China’s A-share market, and the selling amount of margin trading is zero. The number of stocks that are available for margin trading and the number of total listed companies in China’s A-share market are 96 and 2041 at the end of year 2010, respectively. In addition, the margin trading activities increase quickly after 2010. During the whole year 2019, purchasing (selling) amount of margin trading accounts for about 8.94% (0.23%) of the total trading amount in China’s A-share market. The number of stocks that are available for margin trading and the number of total listed companies in China’s A-share market are 1761 and 3857, respectively, at the end of year 2019. During the period from 2010 to 2019, the average percentage of purchasing (selling) amount of margin trading accounts for a total trading amount of about 7.14% (0.52%). Securities margin trading is one important regulation that may have an important impact on China’s A-share market. First, securities margin trading is one important factor affecting arbitraging activities, which are the main mechanism that corrects mispricing and improves capital market efficiency.

Against this background, we want to investigate two issues. First, we want to know whether the idiosyncratic volatility premium puzzle still exists in China’s A-share market as that found by Gu et al. [7] using the sample during 2002 and 2012. Second, can limits to arbitrage measures related to this new background explain this asset pricing puzzle? This paper uses listed stocks in China’s A-share market during 1999 and 2019 as sample to investigate the existence of idiosyncratic volatility premium puzzle in China’s A-share market and whether limits to arbitrage in the new background can explain this kind of asset pricing puzzle.

2. Materials and Methods

2.1. Sample. This paper uses a panel data set consisting of all listed companies in China’s A-share market. Original accounting data and stock trading data are all obtained from RESET data provider, and the variables \( R_{i,t}, \) MKT\(_{t,d} \), SMB\(_{t,d} \), and HML\(_{t,d} \) are used directly. The sample period is from January 2002 to December 2019. Financial sector companies, special treated companies, and companies with missing value are excluded from the original sample.

2.2. Data and Descriptive Statistics. Following Ang et al. [6], stock \( i \)’s idiosyncratic volatility in month \( t \) equals to stock \( i \)’s standard deviation of daily abnormal returns within that month to proxy for stock \( i \)’s idiosyncratic volatility in month \( t \). Stock \( i \)’s daily abnormal returns are calculated based on Fama and French’s [8] three-factor model in month \( t \). Equation (1) is the three-factor model used to calculate individual stock’s daily abnormal return.

\[
R_{i,t} - r_f = \alpha_i + \beta_i \text{MKT}_{t,d} + \gamma_i \text{SMB}_{t,d} + \delta_i \text{HML}_{t,d} + \epsilon_{i,t}.
\] (1)

Equation (1) is used to calculate daily abnormal return on stock \( i \) in day \( d \), where \( R_{i,t} \) is the return on stock \( i \) in day \( d \), \( r_f \) is the risk free rate in day \( d \), and \( \text{MKT}_{t,d} \), \( \text{SMB}_{t,d} \), and \( \text{HML}_{t,d} \) are Fama and French’s [8] three factors in day \( d \). For each stock \( i \), we estimate equation (1) every month and calculate daily abnormal return on stock \( i \) in day \( d \).

The main variables used in this paper include monthly stock return \( (R_{i,t}) \), equal to price change of stock \( i \) in month \( t \) divided by beginning price of stock \( i \) in month \( t \); monthly abnormal stock return \( (AR_{i,t}) \), equal to monthly return of stock \( i \) adjusted by Fama and French’s [8] three-factor model; ratio of equity divided by market value \( (BM_{i,t}) \), equal to equity of company \( i \) at the beginning of the year divided by total market value of its common stock at the beginning of month \( t \); turnover ratio (\( \text{TUR}_{i,t} \)), equal to turnover ratio of tradable common stock during the period from month \( t-5 \) to month \( t \); mean of top 5 maximum daily returns of stock \( i \) in month \( t \) (\( \text{MAX}_{i,t} \)), equal to mean of stock \( i \)’s top 5 highest stock returns within month \( t \); and firm size \( \text{lnMV}_{i,t} \), equal to log of total market value of common stock \( i \) at the end of month \( t \).

Based on China’s A-share market background and regulations, we design the following four variables used to measure limits to arbitrage, three of which are individual measures and the last one is a comprehensive measure which is constructed on the first three measures.

The first one is Amihud [9] illiquidity measure \( (\text{AMH}_{i,t}) \). This measure reflects the effect of trading dollar amount on stock price. The higher value of this measure reflects less liquidity of the stock, and it is more difficult and costly for arbitrageurs to exploit the mispricing opportunity, and the idiosyncratic volatility premium puzzle may be more evident.

The second one is the number of daily closing prices reaching price limits in the last six months \( (\text{PLN}_{i,t}) \). China’s A-share market introduced the price limit regulation which allows for 10 percent price change in the current trading day compared with last trading day’s closing price. Chen et al. [10] argue that price limit regulation hinders price discovery. By intuition, large \( \text{PLN}_{i,t} \) indicates low price efficiency; moreover, it is more difficult for arbitrageurs to correct mispricing, and the idiosyncratic volatility premium puzzle may be more significant.

The third one is the dummy variable proxy for whether margin stock trading is allowed \( (\text{MST}_{i,t}) \). China’s A-share market introduced marginal security trading regulation in 2010, but this regulation is only applied in some of the trading securities. Diamond and Verrecchia [11] believe that short selling constraints hinder price discovery; the price is more efficient in market without short selling constraints. We deduce that idiosyncratic volatility premium puzzle is more significant in stocks with short selling constraints.

The last one is comprehensive measure of limits to arbitrage which is constructed on the above three individual limits to arbitrage measures. We first construct three equal
coefficients for key variables. Panel A shows the descriptive positive. xQ_he mean values of \( \ln MV \) responding skewness values of these variables are all positive. xQ_he median values of these variables, and the corresponding skewness values of these variables are both negative. xQ_he evidence indicates that the smaller than the corresponding median values of these variables are all right skewed, and the distributions of variables \( \ln MV \) and \( \text{MAX}_{i,t} \) are both left skewed. Evidence from panel A tells us that the number of lower returns is less than the number of higher returns.

Panel B shows us the Spearman and Pearson correlation coefficients of main variables. The up-right part is Spearman correlation coefficients and the down-left part is Pearson correlation coefficients. The Pearson correlation coefficients of \( \text{IVOL}_{i,t-1} \), \( \text{BM}_{i,t} \), and \( \text{TURN}_{i,t} \) are all larger than the corresponding median values of these variables, and the corresponding skewness values of these variables are all positive. The mean values of \( \ln MV_{i,t} \) and \( \text{MAX}_{i,t} \) are both smaller than the corresponding median values of these variables, and the corresponding skewness values of these variables are both negative. This evidence indicates that the distributions of variables \( \text{IVOL}_{i,t-1} \), \( \text{BM}_{i,t} \), and \( \text{TURN}_{i,t} \) are all right skewed, and the distributions of variables \( \ln MV_{i,t} \) and \( \text{MAX}_{i,t} \) are both left skewed.

The analysis above tells us the basic characteristics of our sample, and the correlation analysis primarily tells us that stock price idiosyncratic volatility is negatively correlated with next month’s stock return.

### 2.3. Methodology

In Section 3.1, we conduct univariate portfolios analysis and regression analysis to obtain more evidence on the existence of idiosyncratic volatility premium puzzle in China’s A-share market. We construct 5 and 10 portfolios based on \( \text{IVOL}_{i,t} \), and calculate equally weighted and market value-weighted mean of each portfolio’s monthly return. In the regression section, we first construct one asset pricing factor \( \text{IVOLF}_{i,t} \) based on \( \text{IVOL}_{i,t-1} \), introduce this factor into Fama and French’s [8] regression, and conduct Fama and MacBeth’s [12] stepwise regression. The results of these two tests are reported in Tables 2 and 3 , respectively.

In Section 3.2, we conduct two tests to obtain evidence on whether limits to arbitrage can explain idiosyncratic volatility premium puzzle in China’s A-share market. First, we conduct bivariate portfolio analysis based on \( \text{IVOL}_{i,t-1} \) and comprehensive measure of limits to arbitrage \( \text{CM}_{i,t} \). Second, we conduct bivariate portfolio analysis based on \( \text{IVOL}_{i,t-1} \) and individual measures of limits to arbitrage \( \text{AMH}_{i,t} \), \( \text{PLN}_{i,t} \), and \( \text{MST}_{i,t} \). The results of these two tests are reported in Tables 4 and 5 , respectively.

### 3. Results and Discussion

#### 3.1. Empirical Evidence on the Existence of Idiosyncratic Volatility Premium Puzzle in China’s A-Share Market

We conduct univariate portfolios analysis to obtain evidence on the existence of idiosyncratic volatility premium puzzle in China’s A-share market. Each month, all the stocks are sorted into 5 and 10 equal portfolios based on \( \text{IVOL}_{i,t-1} \), respectively. Then, we calculate equally weighted and tradable common stock market value-weighted return of each portfolio. After that, we calculate time series mean of each portfolio return and the corresponding mean return differences between extreme portfolios. Q1 (Q5) stands for portfolios with lowest (highest) \( \text{IVOL}_{i,t-1} \) when constructing five portfolios. \( D_1 \) (\( D_{10} \)) stands for portfolios with lowest (highest) \( \text{IVOL}_{i,t-1} \) when constructing 10 portfolios.

Table 2 reports equally weighted and market value-weighted time series means of each portfolio’s returns, sorted by \( \text{IVOL}_{i,t-1} \). Panel A reports returns of five portfolios sorted by \( \text{IVOL}_{i,t-1} \). These results show that the higher (lower) the \( \text{IVOL}_{i,t-1} \), the lower (higher) the returns of the portfolios. Equally weighted \( R_i \) (\( A_R \)) difference between portfolio Q1 and Q5 is 1.42 (1.51), and the corresponding \( t \)-statistics is 17.09 (24.67). The tradable common stock market value-weighted \( R_i \) (\( A_R \)) difference between portfolio Q1 and Q5 is 0.37 (1.39), and the corresponding \( t \)-statistics is 4.30 (20.32).

Panel B reports returns of ten portfolios sorted by \( \text{IVOL}_{i,t-1} \). These results show that the higher (lower) the \( \text{IVOL}_{i,t-1} \), the lower (higher) the returns of the portfolios. Equally weighted \( R_i \) (\( A_R \)) difference between portfolio \( D_1 \) and \( D_{10} \) is 1.91 (2.04), and the corresponding \( t \)-statistics is 16.20 (23.17). Tradable common stock market value-weighted \( R_i \) (\( A_R \)) difference between portfolio \( D_1 \) and \( D_{10} \) is 0.78 (2.16), and the corresponding \( t \)-statistics is 6.41 (21.95).

In summary, evidence from univariate portfolios analysis tells us that idiosyncratic volatility can negatively predict future stock return; the higher the \( \text{IVOL}_{i,t-1} \), the lower the future stock return. The following regression analysis will provide us with more related evidence.

In the Section 2, we construct idiosyncratic volatility pricing factor \( \text{IVOLF}_{i,t} \). The calculation process used to calculate \( \text{VOLF}_{i,t} \) asset pricing factor consists of the following three steps. First, we sort and construct five portfolios based on \( \text{IVOL}_{i,t} \) each month. Second, we calculate market value-weighted mean return of stocks in each portfolio as the return of that portfolio in that month. Third, we calculate extreme portfolios return difference \( \text{IVOLF}_{i,t} \), equal to
Table 1: Descriptive statistics and correlation coefficients of main characteristic variables.

| Var                    | Mean | Q1  | Q3  | Min | Max | Skew | Kurt |
|------------------------|------|-----|-----|-----|-----|------|------|
| \( AR_{it-1} \)        | -0.00| -0.01| 0.10| -0.06| 0.05| -1.68| 1.22 |
| \( R_{it-1} \)         | 0.01 | -0.00| 0.13| -0.07| 0.08| -0.53| 1.42 |
| IVOLF_{it-1}           | 0.02 | 0.02| 0.01| 0.01| 0.03| 0.00| 0.08 |
| BM_{it-1}              | 0.39 | 0.33| 0.27| 0.21| 0.51| -6.36| 5.43 |
| lnMV_{it-1}            | 21.99| 22.04| 1.26| 21.23| 22.78| 17.46| 28.17 |
| TURN_{it-1}            | 45.49| 34.22| 38.33| 18.83| 59.89| 0.41| 397.90 |
| MAX_{it-1}             | -0.16| -0.14| 0.09| -0.20| -0.10| -0.51| 0.50 |

Panel B: correlation coefficients of main variables (up-right is Spearman, and down-left is Pearson)

| Var                    | \( AR_{it-1} \) | \( R_{it-1} \) | IVOLF_{it-1} | BM_{it-1} | lnMV_{it-1} | TURN_{it-1} | MAX_{it-1} |
|------------------------|-----------------|---------------|--------------|-----------|-------------|-------------|------------|
| \( AR_{it-1} \)        | 1.00            | 0.58***       | -0.09***     | 0.04***   | -0.05***    | -0.08***    | 0.03***    |
| \( R_{it-1} \)         | 0.63***         | 1.00          | -0.01***     | 0.05***   | -0.04***    | 0.01***     | 0.01***    |
| IVOLF_{it-1}           | -0.07***        | -0.01***      | 1.00         | -0.29***  | 0.07***     | 0.46***     | -0.53***   |
| BM_{it-1}              | 0.02***         | 0.03***       | -0.25***     | 1.00      | -0.07***    | -0.27***    | 0.06***    |
| lnMV_{it-1}            | -0.03***        | -0.04***      | 0.07***      | -0.02***  | 1.00        | 0.00        | 0.02***    |
| TURN_{it-1}            | -0.05***        | 0.01***       | 0.41***      | -0.24***  | 0.01***     | 1.00        | -0.41***   |
| MAX_{it-1}             | 0.00***         | 0.02***       | -0.52***     | 0.06***   | 0.01***     | -0.37***    | 1.00       |

Note: ***, ** Statistical significance at 5% and 1% levels, respectively.

Table 2: Mean of equally and market value-weighted portfolios returns when sorted by IVOLF_{it-1}.

Panel A: equally and market value-weighted return of five equal portfolios sorted by IVOLF_{it-1}

| Portfolios | Q1  | Q2  | Q3  | Q4  | Q5  | Q1–Q5 | t-stat |
|------------|-----|-----|-----|-----|-----|-------|-------|
| Equally weighted | \( R_i \) | 1.23*** | 1.28*** | 1.18** | 0.90*** | -0.18** | 1.42 | 17.09 |
| Market value weighted | \( AR_i \) | 1.87*** | 1.97*** | 2.22*** | 2.164*** | 1.51*** | 0.37 | 4.30 |

Panel B: equally and market value-weighted returns of ten equal portfolios sorted by IVOLF_{it-1}

| Portfolios | D1  | D2  | D3  | D4  | D5  | D6  | D7  | D8  | D9  | D10–D1 | t-stat |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|---------|-------|
| Equally weighted | \( R_i \) | 1.19*** | 1.27*** | 1.28*** | 1.29 | 1.25** | 1.11** | 1.06 | 0.73* | 0.35**  | 0.72*** | 1.91 | 16.20 |
| Market value weighted | \( AR_i \) | 0.31*** | 0.33*** | 0.33*** | 0.33 | 0.26*** | 0.16** | 0.10 | -0.02 | -0.65*** | -1.73*** | 2.04 | 23.17 |

Note: *, ** Statistical significance at 10%, 5%, and 1% levels, respectively.

Table 3: Fama and MacBeth [12] regression results.

|                         | Equal weight          | Market value weighted |
|-------------------------|-----------------------|-----------------------|
| Intercept               | 0.003*** (6.83)       | 0.001 (1.38)          |
| IVOLF                   | -0.013*** (−4.50)     | -0.306*** (−4.67)     |
| MKT                     | 0.985*** (98.24)      | 0.972*** (90.32)      |
| SMB                     | 0.777*** (54.30)      | 0.748*** (40.66)      |
| HML                     | -0.257*** (−14.60)    | -0.262*** (−14.76)    |
| Adj_\( R^2 \)           | 49.230                | 50.791                |

Note: ***, Statistical significance at 1% level.

return of the largest IVOLF_{it-1} portfolio minus return of the lowest IVOLF_{it-1} portfolio in each month. Furthermore, we define IVOLF, as the idiosyncratic volatility asset pricing factor. We introduce this IVOLF into Fama and French’s [8] three-factor asset pricing model and conduct Fama and MacBeth’s [12] regression to test the asset pricing effect of the IVOLF. The corresponding stepwise regression results are presented in Table 3.

Table 3 reports the Fama and MacBeth [12] stepwise regression results. We can see that the estimated regression coefficients of IVOLF in equally weighted and market value-weighted regression results are -0.01 and -0.31, respectively, and both are significant at 1% level. What is more, changes of intercept (\( Adj_\( R^2 \) \)) before and after the introduction of VOLF in equally weighted and market value-weighted regression results are 0.00 (1.56%) and 0.00 (1.98%), respectively. All these pieces of evidence above show us that idiosyncratic volatility factor has a significant asset pricing effect.

In summary, the evidence from the descriptive, correlation, and regression analysis proves that stock price idiosyncratic volatility can negatively predict future stock
within each CM

3.2. Empirical Evidence on Whether Limits to Arbitrage Can Explain idiosyncratic volatility premium puzzle in China’s A-share market. In the following section, we will conduct bivariate analysis to obtain evidence on whether limits to arbitrage can explain idiosyncratic volatility premium puzzle in China’s A-share market.

| Table 4: Mean returns of each portfolio sorted by CM_{it} and IVOL_{it−1}. |
|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| CM             | Return          | D1             | D2             | D3             | D4             | D5             | D6             | D7             | D8             |
| L-CM_{it}      | R_{it}          | 1.58           | 1.70           | 1.73           | 1.66           | 1.62           | 1.78           | 1.76           | 1.61           | 1.54           |
|                | AR_{it}         | 0.63           | 0.68           | 0.75           | 0.68           | 0.82           | 0.80           | 0.75           | 0.63           | 0.61           |
| M-CM_{it}      | R_{it}          | 0.91           | 1.10           | 1.21           | 1.21           | 1.11           | 1.14           | 0.86           | 0.68           | 0.61           |
|                | AR_{it}         | 0.10           | 0.28           | 0.38           | 0.28           | 0.21           | 0.19           | -0.09          | -0.28          | -0.31          |
| H-CM_{it}      | R_{it}          | 0.66           | 0.58           | 0.72           | 0.71           | 0.58           | 0.40           | -0.04          | -0.08          | -0.67          |
|                | AR_{it}         | -0.23          | -0.40          | -0.30          | -0.34          | -0.44          | -0.54          | -1.04          | -1.10          | -1.67          |
| L-CM_{it}      | R_{it}          | 1.88           | 1.89           | 2.83           | 2.21           | 2.45           | 2.45           | 2.69           | 2.73           | 2.33           |
|                | AR_{it}         | 0.73           | 0.79           | 1.63           | 0.98           | 1.25           | 1.35           | 1.37           | 1.12           | 1.21           |
| Market value weighted | M-CM_{it} | R_{it}          | 1.67           | 1.68           | 2.04           | 2.37           | 2.02           | 2.13           | 1.71           | 1.73           |
|                | AR_{it}         | 1.23           | 0.93           | 0.99           | 1.08           | 1.06           | 0.77           | 0.20           | 0.22           | 0.19           |
|                |                   |                |                |                |                |                |                |                |                |                |

Table 5: Return differences between extreme IVOL_{it−1} portfolios within different portfolios sorts by individual limits to arbitrage measure.

| Individual limits to arbitrage measures | AMH_{it} | PLN_{it} | MST_{it} |
|----------------------------------------|----------|----------|----------|
| Level of limits to arbitrage            | Returns  | P1−P10   | t-statistics | P1−P10   | t-statistics | P1−P10   | t-statistics |
| Lowest                                 | R_{it}   | 0.85     | 4.14      | 0.51     | 2.97     | 1.45     | 5.58     |
|                                        | AR_{it}  | 1.05     | 7.09      | 0.68     | 5.41     | 1.74     | 8.14     |
| Middle                                 | R_{it}   | 1.44     | 7.12      | 1.34     | 6.42     |          |          |
|                                        | AR_{it}  | 1.46     | 9.83      | 1.31     | 8.42     |          |          |
| Highest                                | R_{it}   | 2.37     | 11.77     | 2.43     | 10.63    | 2.60     | 5.26     |
|                                        | AR_{it}  | 2.54     | 16.11     | 2.39     | 14.05    | 3.04     | 8.18     |

Panel B: market value equally weighted extreme portfolios’ mean return differences

| Individual limits to arbitrage measures | AMH_{it} | PLN_{it} | MST_{it} |
|----------------------------------------|----------|----------|----------|
| Level of limits to arbitrage            | Returns  | P1−P10   | t-statistics | P1−P10   | t-statistics | P1−P10   | t-statistics |
| Lowest                                 | R_{it}   | -1.30    | -5.77     | -0.44    | -2.76    | -0.15    | -0.52    |
|                                        | AR_{it}  | 0.26     | 1.56      | 0.29     | 2.22     | 1.09     | 4.41     |
| Middle                                 | R_{it}   | -0.60    | -2.80     | 0.90     | 3.96     |          |          |
|                                        | AR_{it}  | 0.71     | 4.33      | 0.78     | 4.29     |          |          |
| Highest                                | R_{it}   | 1.49     | 7.05      | 2.68     | 10.57    | 0.51     | 0.89     |
|                                        | AR_{it}  | 3.25     | 18.25     | 2.53     | 12.77    | 5.12     | 11.53    |

return in China’s A-share market. In the following section, we will conduct bivariate analysis to obtain evidence on whether limits to arbitrage can explain idiosyncratic volatility premium puzzle in China’s A-share market.

3.2. Empirical Evidence on Whether Limits to Arbitrage Can Explain Idiosyncratic Volatility Premium Puzzle in China’s A-Share Market. We perform bivariate sorts on CM_{it} and IVOL_{it−1} to obtain evidence on whether limits to arbitrage can explain idiosyncratic volatility premium puzzle in China’s A-share market. In each month, we first constructed low, middle, and high level of limits to arbitrage portfolios sorted by CM_{it} and the three portfolios are indicated by L-CM_{it}, M-CM_{it}, and H-CM_{it}, respectively. Second, we constructed ten portfolios sorted by IVOL_{it−1} within each CM_{it} portfolio every month. D1 (D10) stands for portfolios with lowest (highest) IVOL_{it−1} when constructing 10 portfolios. After this, we constructed thirty portfolios each month. Third, we calculate equally weighted and market value-weighted mean of R_{it} and AR_{it} of the thirty portfolios each month. At last, we calculate the time series mean of equally weighted and market value-weighted return of each portfolio and the time series mean of equally weighted and market value-weighted return difference between extreme portfolios. The results are presented in Table 4.

We can see that the equally weighted mean differences of R_{it} (AR_{it}) between extreme portfolios within low (L-CM_{it}), middle (M-CM_{it}), and high (H-CM_{it}) level of limits to arbitrage portfolios are 0.57 (0.68), 0.93 (1.15), and 2.17 (2.31), and all the differences are statistically significant. What is more, means of R_{it} and AR_{it} are inclined to decrease with the increase of IVOL_{it−1}, in general. This tendency is more evident in portfolios with the highest level of limits to arbitrage. For example, in high level of limits to arbitrage portfolios, the means of AR_{it} from portfolio D1 to portfolio D10 are -0.23, -0.40, -0.30, -0.34, -0.44, -0.54, -1.04, -1.10, -1.67, -2.55, respectively.

We can also find that the market value-weighted mean differences of R_{it} (AR_{it}) between extreme portfolios within low, middle, and high level of limits to arbitrage portfolios are -0.53 (0.14), -0.08 (1.69), and 1.31 (2.81). Except -0.53 and -0.08, all the other differences are statistically significant. This evidence indicates that means of R_{it} and AR_{it} are inclined to decrease with the increase of IVOL_{it−1}, but this
trend is only prevalent in stocks with high level of limits to arbitrage.

In summary, evidence from Table 4 confirms that stock price idiosyncratic volatility in the past few months can negatively predict future month stock return. This predictability is more prevalent in stocks with high level of limits to arbitrage.

To confirm the robustness of the above conclusions, we replace CM with each individual measure of limits to arbitrage and conduct bivariate portfolios analysis. The extreme IVOL portfolios return differences are reported in Table 5.

When limits to arbitrage are measured by AMH, PLN, and MST, respectively, the equally weighted R_{it} (AR_{it}) differences between extreme IVOL_{i,t-1} portfolios are 0.85 (1.05), 0.51 (0.68), and 1.45 (1.74) in the lowest level of limits to arbitrage portfolios, and the values of equally weighted R_{it} (AR_{it}) differences between extreme IVOL_{i,t-1} portfolios are 2.37 (2.54), 2.43 (2.39), and 2.60 (3.04) in the highest level of limits to arbitrage portfolios.

When limits to arbitrage are measured by AMH, PLN, and MST, respectively, the market value-weighted R_{it} (AR_{it}) differences between extreme IVOL_{i,t-1} portfolios are −1.30 (0.26), −0.43 (0.29), and −0.15 (1.09) in the lowest level of limits to arbitrage portfolios, and the values of equally weighted R_{it} (AR_{it}) differences between extreme IVOL_{i,t-1} portfolios are 1.49 (3.25), 2.68 (2.53), and 0.51 (5.12) in the highest level of limits to arbitrage portfolios.

The evidence from Tables 4 and 5 tells us that returns of the lowest IVOL_{i,t-1} portfolio minus return of the highest IVOL_{i,t-1} portfolio are always negative, especially in stocks with high level of limits to arbitrage, and this result is robust. This indicates that idiosyncratic volatility premium puzzle exists in Chinese A stock market, and this effect is more evident in stocks confronting high level of limits to arbitrage.

3.3. Robust Test: Extended Return Period. Table 6 shows us cumulative return (CR_{i,t}) and cumulative abnormal return (CAR_{i,t}) difference between extreme IVOL_{i,t-1} portfolios within low, middle, and high level of limits to arbitrage portfolios when limits to arbitrage measure are CM, and the return periods covered are extended from two to seven months after the portfolios are constructed (n equals 2 to 7 and indicates the number of months after the portfolios are constructed).

When the time period covered is from 2 months to 7 months, the extreme IVOL_{i,t-1} portfolios CR_{i,t} differences are −0.86, −1.00, −1.49, −1.06, −0.45, and −0.5 in low level of limits to arbitrage portfolios, and the corresponding CAR_{i,t} differences are 3.03, 3.51, 4.99, 6.92, 8.06, and 9.97 in high level of limits to arbitrage portfolios. When the time period covered is from 2 months to 7 months, the extreme IVOL_{i,t-1} portfolios CAR_{i,t} differences are 0.23, 0.14, −0.19, −0.05, 0.23, and −0.11 in low level of limits to arbitrage portfolios, and the corresponding CAR_{i,t} differences are 4.79, 5.23, 6.88, 8.44, 10.04, and 11.09 in portfolios with the highest level of limits to arbitrage. In summary, the evidence from Table 6 confirms that the idiosyncratic volatility premium puzzle is robust when extending return periods, and it is likely that the longer the return periods, the more prevalent the idiosyncratic volatility premium puzzle; this tendency is most evident in stocks confronting highest level of limits to arbitrage.

4. Conclusions

This paper proves that idiosyncratic volatility premium puzzle exists during the periods from 2002 to 2019 in the context of China’s A-share market after controlling for size, book-to-market, and systematic risk factors. This effect is robust when we extend the return periods from two months to seven months. When we construct proxies for limits to arbitrage based on Chinese special stock market regulation, we also prove that this idiosyncratic volatility premium puzzle is more prevalent in stocks that are more difficult to arbitrage, which is consistent with the viewpoint that asset pricing puzzle can be explained by limits to arbitrage.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Table 6: Extended periods’ mean return difference of each extreme IVOL portfolio within different portfolios sorts by individual limits to arbitrage measure.

| Returns | CR_{i,t+2} | CR_{i,t+3} | CR_{i,t+4} | CR_{i,t+5} | CR_{i,t+6} | CR_{i,t+7} |
|---------|------------|------------|------------|------------|------------|------------|
| L-CM    | −0.86**    | −1.00*     | −1.49      | −1.06      | −0.45      | −0.55      |
| M-CM    | 0.56**     | 0.89*      | 1.19*      | 2.08**     | 3.26**     | 4.27**     |
| H-CM    | 3.03***    | 3.51***    | 4.99***    | 6.92***    | 8.06***    | 9.97***    |
| H-L     | 3.89***    | 4.51***    | 6.48***    | 7.97***    | 8.51***    | 10.51***   |
| Returns | CAR_{t+2}  | CAR_{t+3}  | CAR_{t+4}  | CAR_{t+5}  | CAR_{t+6}  | CAR_{t+7}  |
| L-CM    | 0.23       | 0.14       | −0.19      | −0.05      | 0.229*     | −0.107     |
| M-CM    | 2.76***    | 3.59***    | 4.46***    | 4.98***    | 6.272***   | 7.184***   |
| H-CM    | 4.79***    | 5.23***    | 6.88***    | 8.44***    | 10.04***   | 11.09***   |
| H-L     | 4.57***    | 5.09***    | 7.07***    | 8.49***    | 9.82***    | 11.19***   |

Note: *, **, ***Statistical significance at 10%, 5%, and 1% levels, respectively.
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