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Margin trading and stock idiosyncratic volatility: Evidence from the Chinese stock market

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ABSTRACT

In this paper, we find that the idiosyncratic volatility (IV) effect on expected returns exists and cannot be explained by other variables in the Chinese stock market. The Chinese stock market launched margin trading in March 2010. We therefore study the margin trading target and non-margin trading target stocks separately and find that the IV effect exists in both stock groups. The IV effect of the margin trading target stocks can be explained by the turnover ratio, whose mechanism shows that the short sale constraint hinders the expression of the seller's heterogeneous beliefs. However, the IV effect of the non-margin trading target stocks cannot be interpreted by other variables. In comparison to margin trading target stocks, non-margin trading target stocks are more likely to have the lottery characteristics and their gambling behavior is more pronounced.

1. Introduction

In the framework of the classic risk-return analysis, investors require corresponding compensation when risks are increasing. Nevertheless, Ang, Hodrick, Xing, and Zhang (2006) document that stocks with a higher idiosyncratic volatility are associated with lower returns in the future. Subsequently, they examine 23 countries and regions and find that this negative relation between idiosyncratic volatility and expected returns still exists internationally (Ang, Hodrick, Xing, & Zhang, 2009). This phenomenon, which is contrary to the classic asset pricing theory, is called the idiosyncratic volatility (IV) puzzle.[1] Later, some scholars confirm this weird phenomenon (such as Stambaugh, Yu, & Yuan, 2015), while other scholars question it (such as Fu, 2009 and Han & Lesmond, 2011). China was not included in the 23 studied regions of Ang et al. (2009). Others later followed the method proposed by Ang et al. (2006): Yang and Han (2009), Zuo, Zheng, and Zhang (2011), and Nartea, Wu, and Liu (2013) estimate the IV and obtain similar results in the Chinese stock market.[2]

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[1] Some recent papers also find a negative relationship between risk and expected returns by applying value-at-risk (VaR) as the proxy for risk, see Atilgan, Bali, Demirtas, and Gunaydin (2020) and Bi and Zhu (2020).

[2] Those who negate the existence of the IV puzzle mainly question it from two aspects: 1) That the estimation method of the expected IV is not correct; and 2) Unreasonable sample selection. Deng and Zheng (2011) use the ARMA model to estimate the IV and believe that there is no IV effect in China's stock market. Fu (2009) applies an EGARCH model to estimate the expected IV because he thinks the method used by Ang et al. (2006) is wrong, in which case, there is no negative relationship between IV and expected returns. However, Guo, Kassa, and Ferguson (2014) argue that the IV estimation in Fu (2009) is incorrect. The EGARCH model established by Fu (2009) uses the return of month t when estimating the IV in month t. Therefore, there is a false positive correlation between the month t's return and IV. To summarize, the controversy over whether the IV effect exists is based on the estimation method of the expected IV and sample selection in the previous papers.

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In the literature, scholars try to explain the idiosyncratic volatility (IV) puzzle. Recently, scholars focus on the arbitrage asymmetry caused by short sale constraint. Stambaugh et al. (2015) believe that the asymmetry of arbitrage leads to the IV effect. Buying undervalued stocks is easier than selling overvalued stocks, so undervalued mispricing is easy to correct while overvalued mispricing is difficult to correct. As a consequence, the stock price is overvalued in general, thus creating an IV puzzle. Chu, Hirshleifer, and Ma (2018) examine the causal relationship between an arbitrage constraint and eleven well-known asset pricing anomalies. The results clearly show that arbitrage limitations enhance the effects of asset pricing anomalies. Yang and Han (2009) suppose that the lack of a short mechanism and the unreasonable structure of the Chinese stock market lead to the IV effect. Zuo et al. (2011) posit that short sale constraint and heterogeneous beliefs are the reasons for the IV effect in the Chinese stock market. Yu, Zhang, and Zhao (2017) believe that heterogeneous beliefs can influence the IV effect and indicate that the introduction of a short mechanism reduces the IV puzzle and heterogeneous beliefs.

Some scholars also try to use the maximum daily returns over the past one month (MAX) to explain the IV effect. Bali, Cakici, and Whitelaw (2011) find a negative and significant relationship between MAX and expected stock returns. They point out that the IV and MAX are highly correlated and that the IV effect could be explained by MAX.[3] A different explanation is proposed by Nartea, Kong, and Wu (2017), who argue that the MAX and IV independently coexist in the Chinese market. Meanwhile, Gu, Kang, and Xu (2018) and Wan (2018) find MAX to be the proxy of IV because MAX can be explained by IV. All these findings are inconsistent with the observations documented in the stock markets of the United States and European countries. Additionally, Liu, Xing, and Zhang (2014) point out that the IV effect no longer exists under the combined effect of price range, MAX, and turnover ratio. The preference for certain special stocks is the main reason for the existence of the IV puzzle.

Based on the above research, we are interested in how short sale constraint, a heterogeneous belief, and gaming behavior influence the IV effect in the Chinese stock market.

China launched a margin trading mechanism in March 2010, which undoubtedly provides a natural experiment for scholars to study the influence of short selling constraints. Many researchers have already studied the impact of margin financing and securities lending on the Chinese stock market.[4] In this paper, we use the last month's IV as the proxy of the current month's IV and study the IV effect in the Chinese stock market. We find that an IV effect exists in the Chinese stock market generally. This article differs from previous research in that we focus on the following two aspects.

First, this article explains the IV effect from heterogeneous beliefs and gambling behavior. The IV is an overall risk measure of abnormal returns. We suspect that gambling behavior and heterogeneous beliefs are the main causes of an IV effect. Kumar (2009) points out that investors prefer lottery-type stocks (stocks that have a low month-end price, high idiosyncratic volatility, and high idiosyncratic skewness), which we call the gambling behavior. Gambling behavior tends to overestimate expected returns, thus leads to abnormal negative returns (see Boyer, Mitton, and Vorkink, 2010; Bali et al., 2011; Conrad, Dittmar, & Ghysels, 2013; Jiang, Wen, Zhou, & Zhu, 2020; Jiang, Wu, Zhou, & Zhu, 2020; among others). In this paper, gambling behavior is represented by MAX; a higher MAX means stronger gambling behavior. A heterogeneous belief means investors have conflicting views on stocks. The stronger the heterogeneous beliefs of investors, we find that stock trading is more active, and the turnover ratio (TURNOVER) of stocks will be higher. Therefore, similar to Zuo et al. (2011) and Liu et al. (2014), we use TURNOVER to represent heterogeneous beliefs, and find that TURNOVER can only explain the IV puzzle within target stocks.

Second, this article explores the impact of short sale constraint on stocks' IV effect. As we know, buying will push the stock price up, while selling will cause the stock price to decrease. Stambaugh et al. (2015) believe that buying is easier than selling, which gives rise to a negative correlation between IV and expected returns due to the existence of the short sale constraint. Li, Xu, and Zhu (2014) believe that the short sale constraint causes stock price overvaluation and that margin trading can mitigate this phenomenon. Li, Du, and Lin (2015) also examine the IV effect of margin trading target stocks and non-target stocks. We will use the margin trading mechanism to study the impact of short sale constraint on stocks' IV effect.

At first, we study the differences in the gambling behavior and heterogeneous beliefs of investors between margin trading stocks and non-margin trading stocks. According to the relevant regulations of the China Securities Regulatory Commission, stocks that become the subjects of margin trading are usually under stricter supervision and are more liquid, less volatile, and have a larger market value. Therefore, the information transparency of margin trading stocks should be higher than other types of stocks, the heterogeneity belief of investors should be weaker, and the gambling behavior will be less. As the result of these findings, our paper further uses the difference-in-differences model to test the effect of margin trading on stocks' IV. Additionally, we speculate that the abnormality of returns caused by heterogeneous beliefs is partially due to the short sale constraint. Because of the asymmetry of buying and selling, buyers can express their own beliefs while sellers cannot. This inevitably leads to an overvaluation of the overall stock price and in turn triggers an abnormal return.

[3] Similarly, Hou and Loh (2016) believe MAX to be another proxy of IV as the time-series average of cross-sectional correlation is as high as 75 percent according to Bali et al. (2011).

[4] For example, Li et al. (2014) use the "plasticizer" incident in the liquor industry to find that a short sale constraint leads to the overvaluation of stock prices, while margin trading helps to correct overvalued stock prices. Li et al. (2015) compare the IV effect of margin trading target stocks (target stock) and non-margin trading target stocks (non-target stock) as well as the IV effect of the stocks before and after the stocks are listed or kicked out. They find that the IV of the target stocks are lower than that of the non-target stocks. The stocks' IV will decrease after the stocks are included in the margin trading institutions and will increase after being excluded (refer to Fu, 2009). Yang, Hua, and Chen (2016) use an EGARCH model to calculate the IV. They classify and discuss both types of margin trading and study their impacts on the stocks' IV effect. They empirically conclude that margin financing will increase the IV effect of stocks, while securities lending will reduce the IV effect of stocks.

This paper has three contributions. First, we find that the IV effect exists in both target stocks and non-target stocks. Note that we are the first paper in the literature illustrating how the IV effect of the margin trading target stocks can be explained by the turnover ratio. Second, we empirically find that the mechanism of IV effect is that the short sale constraint hinders the expression of the seller's heterogeneous beliefs. Yang and Han (2009) speculate that heterogeneous beliefs and short selling restrictions are the reasons for the IV puzzle in Chinese stock market. However, they fail to conduct an empirical test due to the timing of their research since China only just introduced margin trading in 2010. Li et al. (2015) also study target and non-target stocks separately and Yu et al. (2017) use the difference-in-differences model to study the impact of margin trading. What is different in our paper is that we combine these methods and use the difference-in-differences model to test the impact of margin trading on stocks' IV and find that idiosyncratic volatility decreases significantly within target stocks due to China launching a margin trading mechanism. Third, we observe that non-target stocks have stronger lottery features than target stocks.

The remainder of the paper is organized as follows. Section 2 presents the data description and variable definitions. Section 3 provides the major empirical results. Section 4 concludes.

2. Data and variables

The firm-level daily and monthly stocks data are obtained from the CSMAR database. The Fama-French three factors [market (MKT), size (SMB), and value (HML)] come from the China Asset Management Research Center of the Central University of Finance and Economics. Margin trading transaction details are derived from the RESSET database. The institutional shareholding ratio comes from the Wind finance database. The sample includes all A-shares on the Shanghai and the Shenzhen Stock Exchanges. Since the Shanghai and Shenzhen Stock Exchanges began to implement a price limit up-or-down system on December 16, 1996, the sample period is from January 1997 to October 2019. In order to reduce the impact of outliers, we remove any stocks traded on a company's initial public offering (IPO) trading day. The stocks with less than 10 trading days in a month, except for February 1999[5], are also excluded from the volatility calculation in order to ensure accuracy. Due to the constraint imposed by China's price limit system, the up-and-down range of the stock closing price on each trading day is [-10%, 10%] or the closing price of the previous trading day multiplied by 0.9 and 1.1. Therefore, when an abnormal value is deleted, the price fluctuation range is rounded off to two decimal places.

This paper will carry out research on full sample stocks,[6] target stocks, and non-target stocks. A total of 2630 stocks from Shanghai and Shenzhen from January 1997 to October 2019 are selected as our full sample data. In March 2010, China officially launched margin trading and then gradually expanded the size of the margin trading stocks list. Meanwhile, there are also stocks that are removed from the list. In order to guarantee the sample size, we only consider the 429 stocks that have been on the target stocks list since January 25, 2013, until October 2019 as our stock samples for target stocks.[7] The 1159 stocks that never participated in margin trading are used as our stock sample of non-target stocks.[8] Considering the timing of margin financing and the timing of the target stock sample selected, our paper uses the period from January 1997 to March 2010 as the first stage and February 2013 to October 2019 as the second stage. We conduct a comparative study on the two stages before and after margin financing. All variables in the Fama-MacBeth regression are winsorized at 0.5 percent and 99.5 percent to handle extreme values.

We calculate the maximum daily rate of return following the method used by Nartea, Kong, and Wu (2017), which we refer to as MAX. Following Zuo et al. (2011) and Liu et al. (2014), we compute the turnover ratio (TURNOVER) through dividing the monthly cumulative transaction amount by the month-end circulation market value. The idiosyncratic volatility (IV), size (SIZE), book-to-market ratio (BM), the CAPM beta (BETA), short-term reversal (REV), momentum (MOM), and idiosyncratic skewness (ISKEW) are calculated following the methods in Bali, Engle, and Murray (2016). More specifically, the residual standard deviation of the individual stock data obtained by the CAPM model is used to obtain the monthly stock idiosyncratic volatility (IV). In order to ensure the accuracy of the IV, stock data with less than 10 trading days in a month is excluded, except for February 1999. We use last month's standard deviation of the daily return residue to proxy the current month's IV. The size (SIZE) is measured using the natural logarithm of the market value of equity at the end of month *t*. The book-to-market ratio (BM) is the book market value divided by the market capitalization value. The CAPM beta (BETA) is the covariance of stock returns with market returns divided by the variance of market returns. MarBuy is the value of stocks that are bought through financing in one month and SsSell is the value of stocks that are sold through securities lending in one month.

[5] When the transaction is normal, the trading days in February 1999 is less than 10 days; it has only 7 trading days. We therefore exclude stocks with less than 7 trading days in February 1999.

[6] There are 3815 A shares in the China stock market as of October 31, 2019. We remove stocks that have a short sample interval less than 60 months and only keep 2630 of them.

[7] Before February 2013, the Shanghai Stock Exchange had announced a target stock list twice on November 25, 2011 and January 25, 2013, respectively. The Shenzhen Stock Exchange had announced a target stock list four times — on February 12, 2010; June 21, 2010; November 25, 2011; and January 25, 2013. There are 281 stocks in the target stock list on November 25, 2011, and 500 stocks in the target stock list from January 25, 2013. We also exclude stocks that are removed from the target stocks list from January 2013 to October 2019. Thus, in order to guarantee the number of the sample, we choose January 25, 2013 as the starting time.

[8] We only consider stocks that have never participated in margin trading. Once a stock is included in the target stock list, we delete it regardless of the length of time it on the list. There are 2083 stocks meeting our requirement. We also drop stocks with less than 60 trading months, so only 1159 stocks are left.

Table 1
Returns on portfolio sorted by IV.
At the beginning of every month, we sort stocks into quintiles according to their idiosyncratic volatility (IV) in the past calendar month. We compute each portfolio's equal- or value-weighted excess returns for the current month. We also estimate each portfolio's CAPM alpha and Fama-French 3-factor alpha using the full sample of monthly equal- or value-weighted returns for each portfolio. The last two rows show the return and alpha spread between the highest and lowest IV portfolios together with the *t*-statistics which are reported in parentheses. We conduct the analysis for the full sample period from January 1997 to October 2019. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Quintile	EW portfolis			VW portfolis		
	Average return (%)	CAPM alpha (%)	FF-3 alpha (%)	Average return (%)	CAPM alpha (%)	FF-3 alpha (%)
low IV	1.493***	0.741***	0.341***	0.760*	0.143	0.334**
	(2.80)	(4.90)	(3.14)	(1.67)	(0.81)	(2.05)
2	1.597***	0.790***	0.304***	1.084**	0.342*	0.522***
	(2.79)	(4.80)	(3.30)	(2.02)	(1.88)	(2.90)
3	1.436**	0.620***	0.088	0.874*	0.152	0.267**
	(2.47)	(3.57)	(1.16)	(1.72)	(1.11)	(1.97)
4	1.069*	0.240	−0.339***	0.585	−0.177	−0.162
	(1.80)	(1.25)	(-4.43)	(1.07)	(-1.03)	(-0.94)
High IV	0.234	−0.600***	−1.206***	0.009	−0.781***	−0.880***
	(0.38)	(-2.63)	(-9.53)	(0.02)	(-3.83)	(-4.34)
high-low	−1.259***	−1.341***	−1.547***	−0.750**	−0.924***	−1.214***
	(-5.52)	(-6.03)	(-7.78)	(-2.25)	(-2.94)	(-4.13)

3. Empirical test

3.1. IV puzzle in the Chinese stock market

3.1.1. Portfolio analysis

Using a portfolio analysis, stocks are divided into five portfolios according to the IV of each month.[9] We hold these portfolio holdings for one month and update the holding monthly. We then report the equal- (EW) and value-weighted (VW) averages,[10] CAPM alpha, and Fama-French three-factor alpha of stock returns for each quintile as well as the return spread between the highest and lowest IV portfolios in Table 1. The last two rows show the return and alpha spread between the highest and lowest IV portfolios together with the *t*-statistics, which are reported in parentheses. The difference between the equal-weighted (value-weighted) average return of the portfolio for the highest and lowest IV is −1.259% (−0.750% for value-weighted) per month, which is statistically significant at the 5% level. Thus, the IV effect exists and IV is negatively related to the expected returns, which cannot be explained by aforementioned factor models.

3.1.2. Fama-MacBeth cross-section regression

In addition to the single sorting method, we also use the Fama-MacBeth regression analysis at the firm level using monthly data from January 1997 to October 2019. Taking the excess return of the stock as the dependent variable and considering IV, MAX, SIZE, BM, BETA, REV, TURNOVER, MOM, and ISKEW as independent variables, we set up the model as follows:

$$R_{i,t} - r_{f,t} = \beta_{0,t-1} + \beta_{1,t-1}IV_{i,t-1} + \beta_{2,t-1}MAX_{i,t-1} + \beta_{3,t-1}SIZE_{i,t-1} + \beta_{4,t-1}BM_{i,t-1} + \beta_{5,t-1}BETA_{i,t-1} + \beta_{6,t}REV_{i,t-1} + \beta_{7,t-1}TURNOVER_{i,t-1} + \beta_{8,t-1}MOM_{i,t-1} + \beta_{9,t-1}ISKEW_{i,t-1} + \varepsilon_{i,t-1}. \tag{1}$$

We complete a univariate regression analysis first. Table 2 shows the time series average of the regression coefficients for a single variable. The results show that the IV and expected return are significantly negatively correlated, with a *t*-statistic of −7.00, which shows that the IV effect exists in the Chinese stock market. The MAX is significantly negatively correlated with the expected return of stocks, with a *t*-value of −5.94, thus confirming that the Chinese stock market also has a MAX effect. Both findings support the research documented in Nartea, Kong, and Wu (2017). At the same time, SIZE, BETA, REV, TURNOVER, and ISKEW are significantly negatively correlated with the stocks' expected return, BM is significantly positively correlated with the stock's expected return, and there is no significant relationship between MOM and the expected return.

Still focusing on the full sample data, the stock's expected return is used as the dependent variable. A multivariate regression analysis is performed using a Fama-MacBeth regression to test the robustness of the MAX effect and the relationship between MAX and IV. The results are shown in Table 3. We find that IV can explain the MAX since the MAX effect disappears when controlling for IV in the regression. This finding is consistent with Gu et al. (2018), but is different from the work of Nartea, Kong, and Wu (2017), who observe that the MAX effect and the IV effect on the Chinese market independently coexists.

[9] All results are qualitatively similar if we separate stocks into ten portfolios according to their IV.
[10] We use the total market capitalization when calculating the value-weighted averages.

Table 2
All stocks' univariate Fama-MacBeth regression results.
We run a firm-level univariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables using monthly data from January 1997 to October 2019. We report the time series averages of the slope coefficients and their associated *t*-statistics in a single row, but each variable is independently regressed on stock returns. The IV and the other control variables are defined in the Appendix. Significance at the 1% and 5% levels is indicated by ***, and **, respectively.

MAX	SIZE	BM	BETA	REV	TURNOVER	MOM	ISKEW	IV
−0.114***	−0.446***	0.290***	−0.252**	−0.036***	−1.683***	0.001	−0.270***	−0.653***
(-5.94)	(-2.99)	(3.05)	(-2.34)	(-4.00)	(-7.20)	(0.34)	(-5.21)	(-7.00)

Table 3
Full sample data of all stocks' bivariate and multivariate Fama-MacBeth regression results with MAX.
For all stocks, we run a firm-level bivariate and multivariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the MAX and other control variables for the period of January 1997 to October 2019. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. MAX and the other control variables are defined in the Appendix. Significance at the 1% and 5% levels is indicated by ***, and **, respectively.

MAX	SIZE	BM	BETA	REV	TURNOVER	MOM	ISKEW	IV
−0.117***	−0.459***							
(-6.61)	(-3.10)							
−0.109***		0.240***						
(-5.95)		(2.61)						
−0.115***			−0.223**					
(-6.12)			(-2.09)					
−0.113***				−0.016				
(-5.05)				(-1.55)				
−0.051***					−1.500***			
(-2.95)					(-6.79)			
−0.121***						0.002		
(-6.74)						(0.45)		
−0.111***							−0.148***	
(-5.45)							(-2.80)	
−0.030								−0.575***
(-1.46)								(-4.94)
0.051***	−0.689***	0.073	−0.068	−0.018**	−2.501***	0.006**	−0.226***	−0.356***
(3.01)	(-5.34)	(0.98)	(-0.72)	(-2.01)	(-10.67)	(2.17)	(-5.60)	(-4.31)

3.2. Can we explain the IV puzzle?

We will carry out research on full sample stocks, target stocks, and non-target stocks to try to explain the IV puzzle. Again, following our previous practice of taking the full sample from January 1997 to October 2019 and the stock's expected return as the dependent variable, a multivariate regression analysis is performed using a Fama-MacBeth regression to test the robustness of the IV effect. The results are shown in Table 4. When adding other control variables in the regression, the IV effect always exists and cannot be explained by other variables in the Chinese stock market. According to the previous literature, the gambling behavior represented by MAX and the heterogeneous belief represented by the TURNOVER, to a certain extent, can explain IV. However, the results show that after controlling both the TURNOVER and the MAX, although the *t*-value of the IV is greatly reduced (from −7.00 to -2.35), its effect is still significant at the 5% level. This finding indicates that gambling behavior and heterogeneous beliefs cannot fully explain the IV effect. For a multivariate regression, the IV effect remains after all other variables are controlled.

Compared to the non-target stocks, the target stocks have a large market value and high liquidity as well as being less volatile, which means a smaller price fluctuation variance. The corporate information disclosure is also more transparent. Given these facts, the IV effect of the target stocks should be weaker than that of non-target stocks. Therefore, we examine the IV effect of the two types of stocks and also look at how the gambling behavior and heterogeneous beliefs act on the IV effect of the two types of stocks separately.

We use Fama-MacBeth cross-section regressions to analyze both the target stocks and non-target stocks using the period from January 1997 to October 2019. The results are shown in Tables 5 and 6. For target stocks, when the turnover ratio is controlled, the IV becomes completely insignificant (the *t*-value is −0.06; see Table 5), indicating that the heterogeneous beliefs explain the IV effect. For non-target stocks, the situation is similar to the full sample stock in that the IV effect exists and cannot be explained by other variables. The result is documented in Table 6. Both the magnitude and the *t*-value of the IV coefficient are reduced, but are still significant, which means that TURNOVER and MAX cannot fully explain the IV effect.

For the full sample, we find that no variable can explain the IV effect. In addition, the gambling behavior represented by MAX can be explained by IV. The result of non-target and full sample stocks are similar. However, for the target stocks, the IV effect can be explained by TURNOVER, which represents heterogeneous beliefs. TURNOVER can only explain the IV puzzle in the case of target stocks rather than full sample stocks. The main reason for this may derive from the higher risk or volatile of non-target stocks.

Table 4
Full sample data of all stocks' bivariate and multivariate Fama-MacBeth regression results with IV.
For all stocks, we run a firm-level bivariate and multivariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables using monthly data from January 1997 to October 2019. Each row reports the time series averages of the slope coefficients and their associated *t*-statistics. IV and the other control variables are defined in the Appendix. Significance at the 1% and 5% levels is indicated by ***, and **, respectively.

IV	SIZE	BM	BETA	REV	TURNOVER	MOM	ISKEW	MAX
−0.725***	−0.516***							
(-8.48)	(-3.52)							
−0.621***		0.139						
(-6.97)		(1.54)						
−0.665***			−0.221**					
(-7.38)			(-2.12)					
−0.728***				−0.013				
(-7.15)				(-1.29)				
−0.332***					−1.365***			
(-3.63)					(-6.11)			
−0.685***						0.003		
(-7.88)						(0.94)		
−0.641***							−0.187***	
(-6.82)							(-3.70)	
−0.265**					−1.333***			−0.026
(-2.35)					(-6.03)			(-1.29)
−0.356***	−0.689***	0.073	−0.068	−0.018**	−2.501***	0.006**	−0.226***	0.051***
(-4.31)	(-5.34)	(0.98)	(-0.72)	(-2.01)	(-10.67)	(2.17)	(-5.60)	(3.01)

Table 5
Target stocks' bivariate and multivariate Fama-MacBeth regression results with IV.
For target stocks, we run a firm-level bivariate and multivariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables using monthly data from January 1997 to October 2019. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. The IV and other control variables are defined in the Appendix. Significance at the 1% and 5% levels is indicated by ***, and **, respectively.

IV	SIZE	BM	BETA	REV	TURNOVER	MOM	ISKEW	MAX
−0.356***								
(-3.28)								
−0.473***	−0.381***							
(-4.65)	(-2.75)							
−0.354***		0.051						
(-3.50)		(0.37)						
−0.332***			−0.236					
(-3.09)			(-1.57)					
−0.518***				0.004				
(-4.44)				(0.33)				
−0.007					−1.637***			
(-0.06)					(-4.60)			
−0.413***						0.005		
(-3.93)						(1.29)		
−0.354***							−0.087	
(-3.26)							(-1.09)	
−0.352***								−0.021
(-2.75)								(-0.72)
−0.287**	−0.590***	0.061	−0.005	0.003	−2.537***	0.007**	−0.168**	0.042
(-2.24)	(-4.69)	(0.53)	(-0.04)	(0.28)	(-6.54)	(1.99)	(-2.19)	(1.46)

3.3. The impact of a short sale constraint

3.3.1. Comparison of two types of stocks

In order to study the impact of the margin trading mechanism on IV, TURNOVER, and MAX, and to further explore the existence of gambling behavior and heterogeneous beliefs on the two types of stocks, a Fama-MacBeth cross-sectional regression analysis is carried out for both the target stocks and non-target stocks in two stages. The Chinese stock market launched margin trading in March 2010. Our paper takes the period from January 1997 to March 2010 as the first stage and February 2013 to October 2019 as the second stage. The results are shown in Tables 7 and 8. In the second stage, the IV, TURNOVER, and MAX effects of the target stocks are significantly weaker than their effects in the first stage. However, none of the variable coefficient's significance is weakened in the second stage for non-target stocks. If we compare these two different stocks groups, the IV, TURNOVER, and MAX effects are weaker for target stocks than non-target stocks in the second stage, but these variables are similar for target and non-target stocks in the first stage. This finding shows that the IV effect, heterogeneous beliefs, and gambling behaviors of the target stocks can be reduced by margin trading. In comparison,

Table 6
Non-target stocks' bivariate and multivariate Fama-MacBeth regression results with IV.
For non-target stocks, we run a firm-level bivariate and multivariate Fama-MacBeth cross-sectional regression of the return on lagged values of the IV and other control variables using monthly data from January 1997 to October 2019. Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics. The IV and other control variables are defined in the Appendix. Significance at the 1% level is indicated by ***.

IV	SIZE	BM	BETA	REV	TURNOVER	MOM	ISKEW	MAX
−0.900***								
(-9.66)								
−0.927***	−1.179***							
(-10.44)	(-7.33)							
−0.867***		0.263***						
(-9.36)		(2.94)						
−0.928***			−0.087					
(-10.17)			(-0.88)					
−0.898***				−0.029***				
(-9.29)				(-2.92)				
−0.573***					−1.416***			
(-6.06)					(-6.19)			
−0.927***						−0.001		
(-10.38)						(-0.41)		
−0.897***							−0.167***	
(-9.52)							(-2.67)	
−0.819***								−0.030
(-6.96)								(-1.33)
−0.502***					−1.414***			−0.027
(-4.28)					(-6.20)			(-1.17)
−0.376***	−1.527***	0.019	0.002	−0.039***	−2.797***	0.004	−0.193***	0.057***
(-3.98)	(-10.17)	(0.23)	(0.02)	(-4.10)	(-11.16)	(1.33)	(-3.53)	(2.67)

Table 7
Target stocks' two-stage Fama-MacBeth regression results.
We select target stocks for this analysis. On the left-hand side of the Table, we run a firm-level univariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables from January 1997 to March 2010 (first stage). Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics; however, each variable is independently regressed on stock returns. The IV, MAX, and TURNOVER are defined in the Appendix. For the right-hand side of the Table, we run a firm-level univariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables from February 2013 to October 2019 (second stage). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

The first stage			The second stage		
IV	MAX	TURNOVER	IV	MAX	TURNOVER
−0.398***			−0.361*		
(-2.83)			(-1.86)		
	−0.075**			−0.047	
	(-2.15)			(-1.07)	
		−1.702***			−1.520**
		(-4.12)			(-2.64)

Table 8
Non-target stocks' two-stage Fama-MacBeth regression results.
We select non-target stocks. On the left-hand side of the Table, we run a firm-level univariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables from January 1997 to March 2010 (first stage). Each row reports the time-series averages of the slope coefficients and their associated *t*-statistics; however, each variable is independently regressed on stock returns. The IV, MAX, and TURNOVER are defined in the Appendix. For the right-hand side of the Table, we run a firm-level univariate Fama-MacBeth cross-sectional regression of the return on 1-month lagged values of the IV and other control variables from February 2013 to October 2019 (second stage). Significance at the 1% level is indicated by ***.

The first stage			The second stage		
IV	MAX	TURNOVER	IV	MAX	TURNOVER
−0.924***			−0.884***		
(-7.26)			(-5.31)		
	−0.150***			−0.177***	
	(-5.20)			(-5.95)	
		−2.501***			−1.400***
		(-7.01)			(-4.20)

the non-target stocks are almost unaffected by margin trading.

The MAX effect of the non-target stocks is stronger than the target stocks in both stages, indicating that the gambling behavior for the non-target stocks is stronger than that of the target stocks. On one hand, we believe that this result is related to the requirements of investors in the margin trading rules. Both the Shanghai the Shenzhen Stock Exchanges have regulated that investors who open credit accounts must meet the requirements of no less than 500,000 RMB securities trading assets per day for nearly 20 trading days. We call investors who have reached these requirements as qualified investors; all others are called unqualified investors. The investment strength, experience, and analysis level of qualified investors are at a high level and since their investment decisions are more often based on rational analysis, there are probably fewer gambling behaviors. In comparison, unqualified investors exhibit more gambling behaviors. On the other hand, we should note that this result is related to the margin trading choice of target stocks. Through the screening of margin trading rules, the target stocks basically have a large market value, high liquidity, and are less volatile, and so the lottery features of these stocks are weaker. Investors will therefore gamble more on non-target securities. According to Kumar (2009)'s definition, lottery stocks have low prices, high idiosyncratic volatility, and high idiosyncratic skewness. We descriptively test these three characteristics of both the target stocks and non-target stocks and use the independent sample *t*-test to observe the level of significance of the difference. Table 9 shows that the non-target stocks are lower in price, higher in volatility, higher in skewness, and the differences are statistically significant. Therefore, both the nature of stocks and the empirical test indicate that the lottery-type characteristics of the target stocks are weaker and the gambling behavior of the investors for these types of stocks is less.

We suppose that the heterogeneous beliefs of non-target stocks are stronger than those of the target stocks because the heterogeneous beliefs of investors in non-target stocks cannot be expressed. Combining the above-mentioned result that the IV effect of target stocks is explained by the TURNOVER (see Table 5) and the significance of both IV and TURNOVER of target stocks decreases in the second stage (Table 7), we speculate that the introduction of the margin trading mechanism means the investors' heterogeneous beliefs of the target stocks are able to express, thus reducing the IV effect. Next, we further study the impact of the margin trading mechanism on the IV effect of stocks.

3.3.2. *Difference-in-differences model*

Based on the target stocks selection requirement, it's reasonable to have a lower IV. Therefore, due to the company's own characteristics, a simple comparison cannot fully demonstrate that the decrease of the target stocks' IV is due to the introduction of the margin trading mechanism. For the robustness check, we use the difference-in-differences model to test the impact of margin trading on target stocks' IV.

We introduce two dummy variables T and D. T means the time which used to distinguish two periods: before and after the introduction of a margin trading mechanism. We set $T = 0$ for the first stage (from January 1997 to March 2010) when margin trading is not allowed and set $T = 1$ for the second stage (from February 2013 to October 2019) when some stocks are eligible for margin trading. We then create the dummy variable D, which indicates whether a stock is a target stock or not. Let $D = 0$ for the 1159 non-target stocks and let $D = 1$ for the 429 target stocks. Last, we introduce the interaction item $DID = T*D$. If the *t*-value of DID is significant, it reveals that the two kinds of stocks' IV diverge apparently after the introduction of a margin trading mechanism. The model is as follows:

$$IV = \alpha + \lambda_1 T + \lambda_2 D + \lambda_3 DID + \varepsilon, \tag{2}$$

where $\lambda_3$represents the effect of margin trading on the IV.

The results are shown in Table 10. We find that the implementation of margin trading has a significant decreasing effect on the stocks' IV (*t*-value is −38.35). In order to test the robustness of the results, we selected 204 similarly sized stocks from the target stocks and non-target stocks, respectively. We then conduct a difference-in-differences test, common trend test, and placebo test to avoid potential influencing factors after controlling for the size of the stocks.

First, we use a difference-in-differences model after controlling for the size. The results are shown in Table 11. After controlling the scale variable, the IV effect of target stocks is still significantly lower than the IV of the non-target stocks.

Second, we conduct a common trend test. Fig. 1 shows the line chart of an equal-weighted IV for the two types of stocks and time. The line chart from March 2010 to February 2013 is only for the continuity of time and has no practical value. The difference of IV is equal to the IV of the target stocks minus the IV of the non-target stocks. In the first stage, the IV of the two types of stocks is almost exactly the same and the difference of IV is close to zero. In the second stage, the line of difference of IV falls. This finding shows that, in the first

Table 9

Lottery type description statistics.

The table provides descriptive statistics on the price, IV, and ISKEW characteristics of both the target stocks and non-target stocks from five aspects: mean (MEAN), standard deviation (SD), minimum (MIN), median (MEDIAN), and maximum (MAX). We use the independent sample *t*-test to observe the level of significance for the difference. We conduct the analysis using monthly data from January 1997 to October 2019.

	Target stocks			Non-target stocks			Independent sample *t*-test (*t* value)		
	price	IV	ISKEW	price	IV	ISKEW	Price	IV	ISKEW
MEAN	14.95	1.910	0.360	11.80	2.150	0.420	45.872	−75.833	−25.198
SD	20.60	0.950	0.690	9.360	1.050	0.710			
MIN	0.680	0.0200	−3.230	0.150	0.0200	−4.420			
MEDIAN	10.58	1.720	0.340	9.380	1.940	0.390			
MAX	1180	9.030	3.590	370.5	9.550	3.870			

Table 10
Difference-in-differences model.
For the dummy variable T, T = 0 for the first stage (from January 1997 to March 2010) and T = 1 for the second stage (from February 2013 to October 2019). We then create the dummy variable D. Let D = 0 for 1159 non-target stocks and let D = 1 for 429 target stocks. Last, we introduce the interaction item DID = T*D. Significance at the 1% level is indicated by ***.

	IV
DID	−0.343***
	(-38.35)
T	0.152***
	(27.65)
D	−0.095***
	(-15.73)

Table 11
Difference-in-differences model after controlling scale variable.
We select 204 stocks from target stocks and non-target stocks with the closest SIZE, respectively. The settings of the variables are the same as in Table 10. Significance at the 1%, and 5% levels is indicated by ***, and **, respectively.

	IV
DID	−0.110***
	(-7.38)
T	0.001
	(0.12)
D	0.020**
	(2.20)

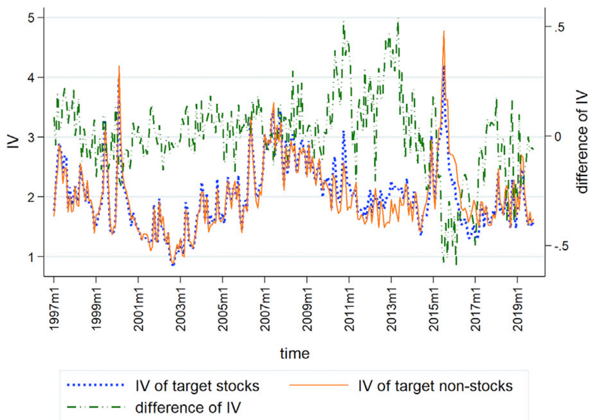

Fig. 1. IV of target stocks and non-target stocks.
The difference of IV is equal to the IV of target stocks minus the IV of non-target stocks.

stage, the two types of stocks have a common trend; in the second stage, after the implementation of the margin trading mechanism, there is a difference between the two types of stocks.

Third, we conduct a placebo test. The sample interval is from January 1997 to February 2010 before financing and securities lending are allowed. If we assume that the margin trading is carried out in January 2003, the first phase is from January 1997 to December 2002 and the second phase is from January 2003 to February 2010. All other variables T and D remain unchanged. The results of the double-difference model are shown in Table 12. Under this condition, the introduction of the margin trading mechanism has significantly increased the IV of target stocks. Therefore, it cannot be said that there are other factors that make the previous results unreliable.

Table 12
Placebo test.
The sample is from January 1997 to February 2010. Assume that the margin trading is carried out in January 2003.The first stage is from January 1997 to January 2003 and the second stage is from March 2003 to February 2010. We select 204 stocks from target stocks and non-target stocks with the closest SIZE, respectively. The settings of the variables are the same as in Table 10. Significance at the 1% level is indicated by ***.

	IV
DID	0.104***
	(5.78)
time	0.373***
	(30.35)
treated	−0.054***
	(-3.88)

In summary, the development of the margin trading mechanism can effectively reduce stocks' IV.

3.3.3. Financing or securities lending

The margin trading can be separated into two different categories: financing and securities lending. In order to explore whether the IV is inhibited by either financing or securities lending, this paper uses SsSell and MarBuy as the proxies for financing and securities lending activities, respectively. MarBuy is the value of stocks that are bought through financing in one month and SsSell is the value of stocks sold through securities lending in one month. We use SsSell and MarBuy as independent variables and the stock's IV as the dependent variable. We then run Fama-MacBeth regressions to test whether SsSell and MarBuy are significantly related to IV. The results are shown in Table 13. We find that SsSell is statistically significant and negatively related with IV, while MarBuy is positively related with IV. This finding indicates that securities lending can effectively reduce IV. When investors borrow money to purchase stocks, they believe these stocks are undervalued. On the other hand, if they lend out their stocks, then they think these stocks are overpriced. When the financing is allowed, it is easy to overestimate the stocks; and when securities lending is allowed, it is easy to underestimate the stocks. The Chinese stock market introduced the securities lending mechanism, which eliminated the short selling constraint for target stocks and reduced their IV. Therefore, the existence of the IV effect of stocks is partially due to the short selling constraint.

According to the research results of Stambaugh et al. (2015) and Li et al. (2014), the short sale constraint will cause arbitrage asymmetry between buyers and sellers. Chu, Hirshleifer, and Ma (2018) also mention that the cost of selling is much higher compared to buying because of the existence of the short selling constraint. We believe that heterogeneous beliefs are normal phenomena in the stock market; otherwise, there would be no trading activities. However, if the heterogeneous beliefs cannot be expressed, we would see an abnormal return. Without margin trading, buying is easier than selling. Thus, the buyer's beliefs are strongly expressed in the market and the seller has no way to express his or her beliefs. As a result, the stock price will be overestimated and generates a negative abnormal return.

Under other similar conditions, the target stocks are more in line with the thought that all investors can obtain sufficient market information in a timely manner in the assumption of the classic capital asset pricing model. Therefore, the market reacts to information more quickly, which can drive the stock price into a reasonable position. Any abnormalities caused by other interference items are weak. When the buying and selling is asymmetric, the seller's belief of shorting is suppressed. After the introduction of the margin financing mechanism, the seller's beliefs can be fully expressed. The IV and TURNOVER of target stocks in the second stage are reduced. Therefore, the IV effect of the margin trading target stock can be explained by heterogeneous beliefs, which is a mechanism showing that the short sale constraint hinders the expression of the seller's heterogeneous beliefs.

Table 13
SsSell and MarBuy Fama-MacBeth regression.
We use target stocks to run a firm-level bivariate and multivariate Fama-MacBeth cross-sectional regression of the IV on the same month values of the SsSell and MarBuy using monthly data from February 2013 to October 2019. The result reports the time-series averages of the slope coefficients and their associated *t*-statistics. IV and the other variables are defined in the Appendix. Significance at the 1% and 5% levels is indicated by *** and **, respectively.

SsSell	MarBuy	SIZE	BM	BETA	REV	MOM	TURNOVER	ISKEW
−4.205***	0.315***							
(-6.24)	(10.74)							
−0.541***	0.018**	0.020**	−0.184***	0.003	0.030***	0.004***	1.381***	0.108***
(-2.75)	(2.27)	(2.57)	(-17.73)	(0.21)	(18.44)	(13.31)	(20.57)	(11.49)

3.4. Robustness test

We conduct a robustness test by eliminating common factors after deleting all financial industry stocks. The financial industry is highly leveraged and has an impact on the outcome; thus, we delete all financial industry stocks at the beginning of the test. We then use a Fama-French three-factor model to eliminate common factors. The formula for the yield is shown in Equation (3). The rate of return comes from two parts: the common factor related return and the abnormal return. After removing the common risk factors [market (MKT), size (SMB), and value (HML)], we get the risk-adjusted rate of return$R_{i,m}_adj$, which is shown in Equation (4).

$$R_{i,m} - r_{f,m} = \alpha_i + \beta_{MKT,i} MKT_m + \beta_{SMB,i} SMB_m + \beta_{HML,i} HML_m + \in_{i,m}. \tag{3}$$

$$R_{i,m}\_adj = \alpha_i + \in_{i,m}. \tag{4}$$

The risk-adjusted rate of return can eliminate the influence of common factors, leaving only the idiosyncratic part and unexplained part to test the robustness of the results. We can therefore avoid the estimation error of the CAPM beta (introduced by Brennan, Chorida, and Subrahmanyam, 1998). We then retest all above-mentioned empirical parts.

The major results are almost consistent with our earlier results, yet there are two differences of note. First, comparing the two relevant time periods discussed in Section 3.1, all IV, MAX, and TURNOVER do not change much for the robust test of the two-stage cross-sectional regression analysis of target stocks.[11] It is hard to see whether the short sale constraint has an impact on the three characteristics. Comparing target and non-target stocks, although with a smaller *t*-value, the significance level of target stocks' IV, MAX, and TURNOVER is the same as the non-target stocks.[12] Second, for the multivariate Fama-MacBeth cross-sectional regression analysis, the *t*-value of SsSell becomes smaller and MarBuy's *t*-value remains similar (see Table IA2 of the Internet Appendix).

Our results are not driven by the estimation method of IV or the sample period for testing the effect. Since the Chinese government implemented a series of rules to control short selling and improve market liquidity in 2015 as the Chinese stock market experiences a significant market decline for that year, we also apply the (Fama and French (1993)) three-factor model to calculate IV and looked at the shorter sample period from January 1997 to December 2014 to conduct additional robustness tests. The main results are still qualitatively similar.[13]

In addition, given the prevalence of noise traders in China, we are also interested in how noise trading affects IV.[14] While it is difficult to gain noise traders' trading data, it is easier for us to gather institutional trading data. We draw a line chart using the year (from 1999 to 2019) as the horizontal axis and the institutional shareholding ratio as the vertical axis. The results are documented in Figure IA1 of the Internet Appendix. Target stocks have a higher institutional shareholding ratio than non-target stocks; they both increase substantially until 2010 and stabilize thereafter. Non-target stocks, with a stronger IV effect, have more noise traders, which is consistent with Aabo, Pantzalis, and Park (2017)'s finding.

4. Conclusion

Overall, an IV effect on the Chinese stock market exists and cannot be explained by other variables. However, if we separate stocks into target and non-target categories, the IV effect of the target stocks can be explained by the turnover ratio. This shows that the IV effect of the target stocks is mainly derived from heterogeneous beliefs, the reason being that the short selling constraint hinders the expression of heterogeneous beliefs. Also, the IV effect of non-target stocks cannot be explained and is largely affected by other factors besides heterogeneous beliefs.

The occurrence of gambling on target stocks is less than that of non-target stocks. On one hand — since the target stocks are in circulation to a greater degree, are more liquid, and less volatile — they are weak in all lottery characteristics. On the other hand, some investors have been subject to a short selling constraint, so they are more likely to gamble on non-target stocks.

Using a difference-in-differences model, we find that the introduction of a margin trading mechanism can significantly reduce the IV of the target stocks. The result remains robust after consideration of several additional tests. The inhibition of the stocks' IV mainly derives from securities lending. Therefore, the introduction of a short selling mechanism is conducive to the stock's price correction in China.

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[11] The results are shown in Table IA1 of the Internet Appendix.
[12] The non-target stocks' results are similar and they are available upon request.
[13] The results are available upon request.
[14] Aabo, Pantzalis, and Park (2017) point out that the larger values of idiosyncratic volatility reflect an increasing role of noise traders.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2020.08.021.

Contribution statement

Pingshu Gui: Conceptualization, Writing- Original draft, Visualization, Software, Data curation. **Yifeng Zhu**: Methodology, Validation, Supervision, Writing- Review & Editing.

Variable definitions

The monthly IV, MAX, and ISKEW data is calculated based on the daily data. The following $i$represents the i-th stock, $d$represents the d-th day, $t$represents the t-th month, $y$represents the y-th year, $R_i$is the return of stock i, $R_m$is the market return, $r_f$is the risk-free return, and $R_m - r_f$is the market return minus the risk-free return.

(1) Idiosyncratic volatility (IV): First, use the CAPM model to find the idiosyncratic return $\varepsilon_{i,d}$of stock $i$on day d.The IV of the t-month of the stock $i$is defined as the standard deviation of the idiosyncratic returns within the month.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i\left(R_{m,d} - r_{f,d}\right) + \varepsilon_{i,d},\ IV_{i,t} = \sqrt{\mathrm{var}(\varepsilon_{i,d})}$$

(2) Maximum daily return (MAX, in percentage points): Due to the influence of the ups and downs in the Chinese stock market, the stock price fluctuations in one day may not be fully expressed. If we use the method of Bali et al. (2011) to find the maximum daily rate of return, it will cause an error. Therefore, following the work of Nartea, Kong, and Wu (2017), this paper seeks the cumulative daily maximum rate of return as a substitute for the maximum daily rate of return. Specifically, if the stock returns hit the upper limit of 10 percent on the first day and 5 percent on the second day, the cumulative return on the first day of the stock is 15 percent. Similarly, if the stock's return on the first day is 10 percent, the yield on the second day is 10 percent, and the return on the third day is 5 percent, then the cumulative return on the first day of the stock is 25 percent.

(3) Short-term reversal (REV, in percentage points): The short-term reversal of period $t$is defined as the return of the previous month $t-1$multiplied by 100.

(4) Momentum (MOM, in percentage points): Following Jegadeesh and Titman (1993), the momentum effect of each stock in month $t$is calculated by the cumulative return over the previous twelve months with one month skipped; i.e., the cumulative return from month t-12 to month t-1.

(5) Size (SIZE, in million RMB): The firm size at each month t is measured using the natural logarithm of the market value of equity at the end of month t.

(6) Book-to-market ratio (BM): The BM is defined as the book market value divided by the market capitalization. We use this to then calculate the logarithm. The twelve months' book market value in year y uses the book market value of month 12 in year y-1. Market capitalization is the market value of equity at the end of month t.

$$BM_{i,t} = \ln\left(\frac{BE_{i,y-1}}{ME_{i,t}}\right),$$

where$BE$is the book market value and$ME$is the outstanding market value.

(7) CAPM beta (BETA): Defined as the monthly covariance of stock i's return and the market return divided by market return variance. Monthly data are used to calculate yearly data,

$$BETA_{i,y} = \frac{\mathrm{cov}(R_{i,t} - r_{f,t}, R_{m,t} - r_{f,t})}{\mathrm{var}(R_{m,t} - r_{f,t})}.$$

(8) Turnover ratio (TURNOVER): Defined as the monthly cumulative transaction amount divided by the market capitalization at the end of the month,

$$TURNOVER_{i,t} = \frac{\mathrm{volume}_{i,t}}{MktCap_{i,t}}.$$

(9) Idiosyncratic skewness (ISKEW): We first calculate the residual of the Fama-French three-factor model, then use the following formula to calculate idiosyncratic skewness:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{MKT,i}MKT_d + \beta_{SMB,i}SMB_d + \beta_{HML,i}HML_d + \in_{i,d},$$

$$ISKEW_{i,t} = \frac{\frac{1}{n}\sum_{d=1}^{n} \in_{i,d}^{3}}{\left(\frac{1}{n}\sum_{d=1}^{n} \in_{i,d}^{2}\right)^{3/2}}.$$

(10) MarBuy: Value of stocks that are bought through financing in a month.
(11) SsSell: Value of stocks that are sold through securities lending in a month. We use the trading share multiplied by the month close price to compute it.

References

Aabo, T., Pantzalis, C., & Park, Jung C. (2017). Idiosyncratic volatility: An indicator of noise trading? *Journal of Banking & Finance, 75*, 136–151.
Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*, 259–299.
Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics, 91*, 1–23.
Atilgan, Y., Bali, Turan G., Demirtas, K. O., & Doruk Gunaydin, A. (2020). Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics, 135*, 725–753.
Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics, 99*(2), 427–446.
Bali, T. G., Engle, R. F., & Murray, S. (2016). *Empirical asset pricing: The cross section of stock returns*. John Wiley & Sons.
Bi, J., & Zhu, Y. (2020). Value at risk, cross-sectional returns and the role of investor sentiment. *Journal of Empirical Finance, 56*, 1–18.
Boyer, B., Todd, M., & Keith, V. (2010). Expected idiosyncratic skewness. *Review of Financial Studies, 23*, 169–202.
Brennan, M.J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, Journal of Financial Economics, 49, 345-373.
Chu, Y., Hirshleifer, D., & Liang, M. (2018). The causal effect of limits to arbitrage on asset pricing anomalies. *The Journal of Finance*. Forthcoming.
Conrad, J., Dittmar, R. F., & Ghysels, E. (2013). Ex ante skewness and expected stock returns. *The Journal of Finance, 68*, 85–124.
Deng, X., & Zheng, Z. (2011). Is there an idiosyncratic volatility puzzle in China's equity market? *Journal of Business Economics, 231*, 60–67.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.
Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics, 91*(1), 24–37.
Gu, M., Kang, W., & Xu, B. (2018). Limits of arbitrage and idiosyncratic volatility: Evidence from China stock market. *Journal of Banking & Finance, 86*, 240–258.
Guo, H., Kassa, H., & Ferguson, M. F. (2014). On the relation between EGARCH idiosyncratic volatility and expected stock returns. *Journal of Financial and Quantitative Analysis, 49*(1), 271–296.
Han, Y., & Lesmond, D. (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. *Review of Financial Studies, 24*(5), 1590–1629.
Hou, K., & Loh, R. K. (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics, 121*(1), 167–194.
Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65–91.
Jiang, L., Wen, Q., Zhou, G., & Zhu, Y. (2020a). *Lottery preference and anomalies*. Working Paper.
Jiang, L., Wu, K., Zhou, G., & Zhu, Y. (2020b). Stock return asymmetry: Beyond skewness. *Journal of Financial and Quantitative Analysis, 55*(2), 357–386.
Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance, 64*, 1889–1933.
Li, Z., Du, S., & Lin, B. (2015). Short selling and stock-price stability: A natural experiment from the margin trading market of China. *Journal of Financial Research, 6*, 173–188.
Liu, W., Xing, H., & Zhang, X. (2014). Investment preference and the idiosyncratic volatility puzzle: Evidence from China stock market. *Chinese Journal of Management Science, 22*(8), 10–20.
Li, K., Xu, L., & Zhu, W. (2014). Short-sale constrains and stock mispricing: The evidences from the margin transactions institution. *Economic Research Journal, 10*, 165–178.
Nartea, G. V., Dongmin, K., & Ji, W. (2017). Do extreme returns matter in emerging markets? Evidence from the Chinese stock market. *Journal of Banking & Finance, 76*, 189–197.
Nartea, G. V., Wu, J., & Liu, Z. (2013). Does idiosyncratic volatility matter in emerging markets? Evidence from China. *Journal of International Financial Markets, Institutions and Money, 27*, 137–160.
Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance, 70*(5), 1903–1948.
Wan, X. (2018). Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market. *International Review of Economics & Finance, 53*, 1–15.
Yang, H., & Han, L. (2009). An empirical study of the relationship between the idiosyncratic volatility and cross-sectional return. *Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition), 22*(1), 6–10.
Yang, H., Hua, S., & Chen, S. (2016). An empirical study on the impact of margin trading on stock market idiosyncratic volatility. *Shanghai Finance, 1*, 73–77.
Yu, W., Zhang, B., & Zhao, L. (2017). Heterogeneous information, short selling and the idiosyncratic volatility puzzle based on the evidence from 2,698 listed companies from China's A stock market. *Finance and Economics, 347*(2), 38–50.
Zuo, H., Zheng, M., & Zhang, Y. (2011). Stock volatility and cross-sectional returns: An explanation of the "mystery of trait volatility" in China's stock market. *Journal of World Economy, 34*(5), 117–135.