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The impact of idiosyncratic volatility on the investors' herd behavior in the Chinese Stock Market

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Abstract: This study provides a comprehensive study of herding behavior in the Chinese Stock Market using the cross-sectional absolute deviation of returns method (CSAD) proposed by (Chang et al., 2000), which captures the non-linearity relationship between the dispersion of individual returns and market return. According to (Christie & Huang, 1995) and (Chang et al., 2000), in a stock market, herding behavior occurs when individual returns begin to converge towards the consensus of the market, leading to a decrease in the dispersion of stock return from the market return. More particularly, this study inspects the impact of idiosyncratic volatility on the investors' herd behavior in the Chinese Stock Market by delving deeper into the nature of herding and its asymmetric effect under extreme market conditions and at various stages of idiosyncratic volatility, as well as herding frequency and its asymmetric effect in increasing and falling markets. The results of this study indicate that idiosyncratic volatility is an essential component and determinant of herding conduct. The findings indicate that herding occurs in the Chinese stock market, and exhibits diverse patterns under different equity portfolios according to the levels of idiosyncratic volatility as well as the market trend, and that investment behavior tends to be different during three sub-periods. Moreover, the findings document that Financial Crisis period increases herding, especially within stock portfolios with higher idiosyncratic volatility.

Keywords: Herding Behavior, Idiosyncratic Volatility, Portfolio Construction, Chinese Stock Market, CSAD, Sub-period Analysis.

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1. Introduction

The dynamics of the financial markets have become a real challenge for most of the researchers. The financial markets are still puzzling and almost defy all conventional asset pricing models, particularly during severe turbulent events, despite thorough studies in explaining the asset price movement. The conventional asset pricing theory, in which the "Capital Asset Pricing

Model (CAPM)" is the most well-known mainstream finance model, has demonstrated weakness in describing fluctuations in asset prices and the instability of excess returns on financial markets following the aftermath of global financial crises and market turbulence. Indeed, when the traditional financial concepts fail to explicate the asset price movements, scholars are more liable to find answers in the behavioral finance theory.

Behavioral finance is a modern way of looking at the stock market that has established more practical and rational reasons for market volatility based on a blend of social and cognitive psychological theory with conventional economics and finance in response to difficulties faced by the traditional paradigm. "The behavioral theory explanation assumes that investors' reaction to events fuelling market variation is more influential than the events themselves" (Litimi et al., 2016). In other words, as argued by (Jyoti Kumari, 2015), the volatile emotions and beliefs of the investors play a significant role to predict the future volatility. In the same line, (BenSaïda, 2017) assume that the driving force of the excessive market volatility in the U.S. Stock Market is essentially the investors' trading behavior, more particularly, the behavior of herd.

According to the classical asset pricing models, an investor can only bear the systematic risk, also called market risk, and can only mitigate the firm-specific risk, also called idiosyncratic volatility risk, through portfolio diversification. While, idiosyncratic volatility can be lessened in a well-diversified portfolio, investors may still care about the "unsystematic risk" of the financial assets that they hold. By the reason of wealth constraints or by subjective choices, many investors do not hold diversified portfolios (Xu & Malkiel, 2003). As a consequence, undiversified investors claim compensation to endure the idiosyncratic volatility risk (Merton, 1987). Moreover, (Levy, 1978) contends that the idiosyncratic volatility plays a critical role in determining the asset price equilibrium when investors hold few stocks in their stock portfolios. (Malkiel & Xu, 2006) confirm that higher idiosyncratic volatility portfolios have higher average returns because investors who are unable to maintain a completely diversified portfolio want return compensation. (Spiegel & Wang, 2005) confirmed the latter argumentations by finding a positive relationship at the firm level between expected returns and expected idiosyncratic volatility.

There is a growing study that has paid considerable attention to the phenomena of idiosyncratic volatility and has provided theoretical and empirical evidence that idiosyncratic volatility matters (Campbell et al., 2001); (Malkiel & Xu, 2006), and should be priced and included in the financial asset pricing models. Therefore, one can argue that the idiosyncratic volatility has a price (Ang et al., 2006); (Ang et al., 2009); (Bali & Cakici, 2009) and (Campbell et al., 2001). Therefore, the particular risk of the securities they hold is still of interest to investors. That is to say, idiosyncratic volatility still necessitates further study in academic research.

Furthermore, when undiversified investors face the risk of information scarcity, the idiosyncratic volatility of their stocks increases and the herding behavior occurs. Non-transparency, according to (Bikhchandani et al., 1992), is one of the key factors that contributes to herding. As a consequence, a better understanding of the relationship between idiosyncratic volatility and herd behavior is needed and recommended.

In a broader sense, herd behaviour is a concept used in economics and finance to characterize a mechanism in which market participants ignore their own values in order to mimic each other's opinions, emotions, and behaviors, and base their decisions on the actions of other investors (Spyrou, 2013). According to (Bikhchandani & Sharma, 2001), herding behavior emerges from a noticeable desire by investors to replicate the behavior of other investors. (Nofsinger & Sias, 1999) define the "herding behavior as a group of investors who trade in the same direction over a period of time. (Hwang & Salmon, 2004) describe the herding behavior as a form of harmonized and homogenous behavior". (Avery & Zemsky, 1998) define the herd as the process by which investors suppress the initial valuation and act in accordance with the trend in the preceding trade.

This study defines herding behavior as the process whereby individual investors exhibit a mimicking behavior of the actions of others and a preference for compatibility with the market consensus (Devenow & Welch, 1996); (Galariotis et al., 2015); (Galariotis et al., 2016) and (Indārs et al., 2019).

The institutional characteristic of the Chinese Stock Market, in which the study examines herding behavior in both the Shanghai Stock Exchange (S.H.S.E) and Shenzhen Stock Exchange (S.Z.S.E), plays a crucial role for the first pillar motivation of this study. The Chinese Stock Market's unique macro/micro-structure features yield an important background for the investigation of investor herding behavior. In recent years, the Chinese government has enacted various courses of action to reform the stock market, but it is still widely criticized for its lack of transparency, large scale of unsophisticated retail investors, heavy idiosyncratic volatility, and substantial protocols. Hence, in comprehending of how investors act in the Chinese Stock Market is important and worthwhile. The second motivation is manifested by the characteristic of asymmetric information in the framework of emerging markets. (Gelos & Wei, 2005) argue to the fact that emerging markets are characterized by lower transparency and higher information asymmetries, provide sufficient motivation to investors to recourse to herding. The third motivation stems from the lack of articles that take into account herd behavior in the sense of idiosyncratic volatility or firm-specific risk. In the existing literature, a comprehensive attempt has been made to research idiosyncratic volatility. Most previous study, on the other hand, focused on analyzing the problem under the presumption that investors are rational, ignoring the significance of investor actions.

Despite that, (Huang et al., 2015) and (Vo & Phan, 2019a) argued that when undiversified investors emulate other market participants' decision-making strategies, the idiosyncratic volatility could have a major effect on herding conduct. Few studies deliver a direct connexion of herding response to the effect of idiosyncratic volatility (Chang & Dong, 2006); (Dennis & Strickland, 2004) and (Fernandez, 2014). As a result, this study performs a sub-period analysis at the market level to explore the effects of idiosyncratic uncertainty on herding behavior in greater depth. Furthermore, this study explores the effects of idiosyncratic volatility on herding behavior in greater detail, by looking into the nature of herding and its asymmetric influence under extreme market conditions and market dynamics (falling and rising markets), conducting a sub-period analysis focused on the Great Financial Crisis, and constructing a portfolio based on idiosyncratic volatility. The majority of studies look at idiosyncratic volatility through the prism of investor rationality, ignoring the behavioral element of it, and only a few studies show a clear correlation between idiosyncratic volatility and herding conduct. As a consequence, a deeper understanding of the relationship between idiosyncratic volatility and herd behavior is essential. The results of this study indicate that idiosyncratic volatility is an essential component and determinant of herding conduct. The findings indicate that herding occurs in the Chinese stock market, that it differs with idiosyncratic volatility, and that investment behavior tends to be different during three sub-periods.

The remainder of this research is structured as follows. The analysis of literature on herd behavior and idiosyncratic volatility is outlined in Section 2. The data and methods that will be used are discussed in Section 3. Section 4 describes empirical observations on the occurrence of herding activity at different levels of idiosyncratic instability. Finally, conclusion.

2. Related literature

In the aftermath of various global financial meltdowns, herding conduct has gained worldwide attention from academia and the financial literature. Herd activity, according to (Bikhchandani & Sharma, 2001); (Spyrou, 2013) fuels market uncertainty and contributes to financial instability. The role of herding in both advanced and developing markets has been studied extensively (Christie & Huang, 1995); (Chang et al., 2000); (Guney et al., 2017); (Demirer & Kutan, 2006); (Galariotis et al., 2015);(Galariotis et al., 2016); (Chiang & Zheng, 2010) and (Vo & Phan, 2019a); (Vo & Phan, 2019b). Moreover, there is a substantial body of literature that has examined the herding behavior and total volatility, only a few studies indicate a direct effect of idiosyncratic volatility on herding behavior.

The behavior of the volatility of the market has been widely studied in the financial literature. However, less attention has been devoted to the behavior of the volatility of individual stocks. (Xu & Malkiel, 2003) state that the stock-specific risk can increase even when the market-risk as a whole remains stable. As a consequence, it is both worthwhile and desirable to obtain a deeper understanding of the relationship between herding conduct and idiosyncratic volatility.

Using Japanese data from 1975 to 2003, (Chang & Dong, 2006) study the cross-sectional relationship between idiosyncratic volatility of individual firms, institutional herding, and firm earnings and provide empirical evidence at both portfolio level and firm level that variations in idiosyncratic volatility are related to both fundamental and behavioral factors. More specifically, the findings show that both firm earnings and institutional herding are positively and significantly linked to idiosyncratic volatility. Thus, the argument of the behavior story confirms its key role in explaining the different patterns of market aggregate idiosyncratic volatility.

From a different viewpoint, (Huang et al., 2015) examine the effects of idiosyncratic uncertainty on individual investors' investment activity in the Taiwanese stock market from 2004 to 2013. The empirical findings indicate that herd behavior occurs in the Taiwan Stock Market, and that it takes various forms depending on the degree of idiosyncratic volatility. Herding activity occurs in stock portfolios with higher idiosyncratic volatility, but not in stock portfolios with lower idiosyncratic volatility, according to the empirical findings. In contrast, (Vo & Phan, 2019a) analyze the effect of idiosyncratic volatility on individual investor herd activity using data from the Vietnam stock market from 2005 to 2016. Under varying degrees of idiosyncratic volatility, empirical evidence confirms the occurrence of herding conduct. Herding activity is more likely to be stronger and important in stock portfolios with the lowest idiosyncratic volatility than in stock portfolios with the highest idiosyncratic volatility.

Many individual investors refer stocks with strong idiosyncratic risk features as stocks that are problematic to estimate their price value, such that it is better for individual investors to pursue skilled and sophisticated investors' trading strategies. (Wibowo, 2019) claims that herd activity appears to be much stronger in stock groups which have high idiosyncratic volatility in the Indonesia stock exchange. More particularly, he suggests that herd occurs in normal periods and not during crisis.

A branch of literature has also provided evidence that financial crises affect herding formation (Chiang & Zheng, 2010) and (Galariotis et al., 2015). For instance, (Indārs et al., 2019) use data covering from 2008 to 2015 Moscow stock Exchange, they show that the total herding is appearing during the period of the Subprime crisis and during the Crimea's annexation, but no herding was evidenced during the Russian crisis. However, (Hwang & Salmon, 2004) studied the herding behavior in both U.S. and Korean Stock Markets, their empirical evidence reports that herding is reduced during the Asian crisis and especially during the Russian crisis.

Indeed, the impact of extreme events on traders' investment strategies affects the behavior of the herd. (Huang et al., 2015) show that the 2007 / 2008 financial crisis augments herding behavior, in particular portfolios with larger idiosyncratic volatility. Whereas, (Vo & Phan, 2019a) provide evidence of herding in three sub-groups: BFC, FC and AFC within various levels of idiosyncratic volatility of each individual stock. Herding activity is thought to be more common in stock portfolios with the lowest idiosyncratic volatility than in stock portfolios with the highest idiosyncratic volatility. Therefore, inspiring from the above literature, this study will investigate the pattern of herding behavior and idiosyncratic volatility during major financial meltdowns. In addition, it is also important to examine the herding behavior under different market conditions and investigate the asymmetry effect of the herding as well (Huang et al., 2015); (Chiang & Zheng, 2010) (Galariotis et al., 2015); (Indārs et al., 2019) and (Vo & Phan, 2019a). Therefore, a further empirical investigation might deliver a critical understanding to the linkage of the behavior of herding and idiosyncratic volatility in this regard.

None of the studies that investigates the relationship of herding and idiosyncratic volatility in the context of the Chinese Stock Market, so it is believed that this is the first study of its kind in the Chinese Stock Market. Besides, some of the studies that have been done in other markets, incorporate idiosyncratic volatility into the non-linear model, however the particularity of this study is manifested by building a portfolio-based idiosyncratic volatility in which herding intensity is examined more deeply. Furthermore, many of the studies examine idiosyncratic volatility in a context of rationality, and fail to consider the behavior bias. More particularly, this study explores the effects of idiosyncratic volatility on herding behavior in greater detail, by looking into the nature of herding and its asymmetric influence under extreme market conditions and market dynamics, conducting a sub-period analysis focused on the Great Financial Crisis.

3. Data Collection & Methodology

3.1 Data Collection

The dataset consists of all A- Shares and B- Shares listed Shanghai Stock Exchange (S.H.S.E) and the Shenzhen Stock Exchange (S.Z.S.E) over the period from January 1, 2003 through December 31, 2018. All data is obtained from the China Stock Market & Accounting Research

(C.S.M.A.R) database. It is widely assumed that herding behavior is a very short-lived phenomenon (Christie & Huang, 1995). So, to deepen the understanding of the distinct pattern of the herding behavior, the study will provide a comprehensive analysis by using daily frequency. Therefore, the sample will include data of both firm-specific returns and market-level returns on a daily frequency. Because B- Shares are denominated in "U.S. dollars" or "Hong Kong dollars" for Shanghai B- and Shenzhen B- Shares, respectively, the returns on B-Shares will be adjusted for exchange rate effects.

3.2 Methodology

3.2.1 Idiosyncratic Volatility Estimation

To estimate the idiosyncratic volatility, this study employs the single factor model of (Bali & Cakici, 2009)1.

$$\boldsymbol{R_{i,t} = \beta_0 + \beta_1 R_{m,t} + \varepsilon_{i,t}} \qquad \text{Eq: 1}$$

$$\boldsymbol{Idiovolati_{i,t} = \left(Var(\varepsilon_{i,t})\right)^{1/2}} \qquad \text{Eq: 2}$$

Where N is the number of firms in the portfolio, $R_{m,t}$ is the market return at time t, and $R_{i,t}$ is the stock return of firm i at time t. $\varepsilon_{i,t}$ is regression residuals of stock i at time t. $Idiovolati_{i,t}$ represents the idiosyncratic volatility of individual stock i, which is the standard deviation of residuals at time t.

3.2.2 Portfolio based-Idiosyncratic Volatility Construction

To investigate, to which extent idiosyncratic volatility affects herding behavior, this study perform a sub-period analysis, the first period is the before financial crisis (BFC) period which starts from 2003/01/01 to 2007/06/30, the second period is of financial crisis (FC) which starts from 2007/07/01 to 2008/12/31, and finally the period after the crisis (AFC) which starts from 2009/01/01 to 2018/12/31, then the study splits the sample into three main groups giving the level of the idiosyncratic volatility of each stock. Group 1, will contain stocks with the smallest idiosyncratic volatility, while Group 3, will contain stocks with the biggest idiosyncratic volatility.

3.2.3 Herding Intensity Estimation

To estimate the presence of herding behavior, this study follows the non-linear model of the cross-sectional absolute deviation of returns method (CSAD) advanced by (Chang et al., 2000).

$$\boldsymbol{CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t} \qquad \text{Eq: 3}$$

Thus, a negative and statistically significant coefficient β_2 infers the decrease of return dispersion from market returns which indicates the incidence of herding.
Similarly, this study checks for herding behavior in periods of extreme market conditions by employing CSAD measure.

$$\boldsymbol{CSAD_t = \beta_0 + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t} \qquad \text{Eq: 4}$$

[1] "For each of the stock markets, Shanghai A (S.H.S.A), Shanghai B (S.H.S.B), Shenzhen A (S.Z.S.A) and Shenzhen B (S.Z.S.B), the idiosyncratic volatility is estimated."

Where $D_t^L = 1$, if the market return at day t, situates in the extreme "lower tail of the returns distribution, and 0 otherwise. $D_t^U = 1$, if the market return at day t, lies in the extreme "upper tail" of the returns, and 0 otherwise. A statistically significantly negative values of β_1 and β_2 indicate the presence of herding. This study uses the 1%, 5% criterion of the market return, to express the utmost market movements.
To inspect the asymmetric effect of herding under "up and down markets", the following model is specified:

$$\boldsymbol{CSAD_t^{DOWN}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}^{\boldsymbol{DOWN}}\left|\boldsymbol{R_{m,t}^{DOWN}}\right| + \boldsymbol{\beta_2}^{\boldsymbol{DOWN}}\left(\boldsymbol{R_{m,t}^{DOWN}}\right)^2 + \boldsymbol{\varepsilon_t}, \text{ where } \boldsymbol{R_{m,t}} < \boldsymbol{0} \qquad \text{Eq: 5}$$

$$\boldsymbol{CSAD_t^{UP}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}^{\boldsymbol{UP}}\left|\boldsymbol{R_{m,t}^{UP}}\right| + \boldsymbol{\beta_2}^{\boldsymbol{UP}}\left(\boldsymbol{R_{m,t}^{UP}}\right)^{\boldsymbol{2}} + \boldsymbol{\varepsilon_t}, \text{ where } \boldsymbol{R_{m,t}} > \boldsymbol{0} \qquad \text{Eq: 6}$$

Where $CSAD$ is the dependent variable. $\left|R_{m,t}^{UP}\right|$ and $\left|R_{m,t}^{DOWN}\right|$ are the "absolute values of average market returns in up and down markets", respectively $\left(R_{m,t}^{UP}\right)^2$ and $\left(R_{m,t}^{DOWN}\right)^2$ are the corresponding quadratic terms.

4. Empirical Results

4.1 Descriptive Statistics of CSAD

Table 1 summarizes the descriptive statistics of CSAD for the Shanghai A (S.H.S.A), Shanghai B (S.H.S.B), Shenzhen A (S.Z.S.A), and Shenzhen B (S.Z.S.B) stock markets , for the complete sample duration and three sub-periods. This metric depicts how individual stock returns cluster around market returns. High values of CSAD mean that returns are less clustered around market returns. Low values of CSAD values, on the other hand, indicate more clustered returns around market returns. Furthermore, the higher level and variability of dispersion of return in a given time can indicate different trading trends among traders at that time.
In all the periods, the average values of CSAD of Shanghai A (S.H.S.A) are all marginally greater than zero, indicating that individual stock returns shift in synch with market returns. Furthermore, the mean CSAD rises from 0.000011 in the BFC period to 0.000027 in the FC period, with a standard deviation of 0.000033 with a standard deviation of 0.000042, and increases again to 0.000414 in the AFC period accompanied by a higher standard deviation of 0.000550, indicating that herding in Shanghai A (S.H.S.A) is probable to be more marked in FC period. For Shanghai B (S.H.S.B), the mean CSAD increases from 0.000246 in the BFC period accompanied by a standard deviation of 0.000294, to 0.00029 in the FC period with a standard deviation of 0.000301, and decreases to 0.000188 in the AFC period accompanied by a standard deviation of 0.000240, indicating that herding in Shanghai B (S.H.S.B) is probable to be more marked in AFC period. For Shenzhen A (S.Z.S.A), the mean CSAD increases from 0.000028 in the BFC period accompanied by a standard deviation of 0.000056, to 0.000033 in the FC period with a standard deviation of 0.000098, and decreases to 0.000012 in the AFC period accompanied by a standard deviation of 0.000025, indicating that herding in Shenzhen A (S.Z.S.A) is probable to be more noticeable in AFC period. For Shenzhen B (S.Z.S.B), the mean CSAD increases from 0.000269 in the BFC period accompanied by a standard deviation of 0.000276, to 0.000307 in the FC period with a standard deviation of 0.000303, and decreases to 0.000207 in the AFC period accompanied by a standard deviation of 0.000236, indicating that herding in Shenzhen B (S.Z.S.B) is probable to be more distinct in AFC period.

Overall, the values of CSAD values are decreasing from the BFC to the AFC period, suggesting that herding activity is more apparent in the AFC period. Furthermore, as the standard deviations reflecting return dispersion variability increase from BFC to AFC, it suggests that there are more diverse investment trends among investors during periods with high standard deviations.

		Full sample Period		*BFC* Period		*FC* Period		*AFC* Period	
Markets		Equal-Weighted Market return	*CSAD*	Equal-Weighted Market return	*CSAD*	Equal-Weighted Market return	*CSAD*	Equal-Weighted Market return	*CSAD*
S.H.S.A	Mean	0.000624	0.000011	0.000964	0.000020	-0.000822	0.000027	0.000687	0.000414
	Std.dev	0.019574	0.000017	0.017536	0.000033	0.030722	0.000042	0.018424	0.000550
	Min	-0.096800	0.000000	-0.085800	0.000000	-0.088000	0.000000	-0.096800	0.000000
	Max	0.095800	0.007808	0.076900	0.013899	0.09570	0.013869	0.095800	0.267986
S.H.S.B	Mean	0.000538	0.000215	0.000995	0.000246	-0.001763	0.000290	0.000687	0.000188
	Std.dev	0.019730	0.000265	0.021239	0.000294	0.029230	0.000301	0.016918	0.000240
	Min	-0.099800	0.000000	-0.089200	0.000000	-0.090900	0.000000	-0.099800	0.000000
	Max	0.107600	0.026834	0.107600	0.019170	0.094500	0.003358	0.100100	0.026834
S.Z.S.A	Mean	0.000744	0.000013	0.000963	0.000028	-0.001055	0.000033	0.000861	0.000012
	Std.dev	0.020520	0.000027	0.017810	0.000056	0.031144	0.000098	0.019810	0.000025
	Min	-0.097800	0.000000	-0.085300	0.000000	-0.088600	0.000000	-0.097800	0.000000
	Max	0.099100	0.015477	0.075700	0.021075	0.097400	0.022843	0.099100	0.015570
S.Z.S.B	Mean	0.000572	0.000236	0.001087	0.000269	-0.002029	0.000307	0.000750	0.000207
	Std.dev	0.017779	0.000258	0.018779	0.000276	0.025200	0.000303	0.015600	0.000236
	Min	-0.098900	0.000000	-0.090200	0.000000	-0.086000	0.000000	-0.098900	0.000000
	Max	0.100200	0.008513	0.091200	0.003343	0.092500	0.003276	0.100200	0.008513

Table 1: Descriptive Statistics of CSAD.

"**Notes**: This table presents the descriptive statistics on *cross-sectional absolute deviation* of returns (*CSAD*), *Equal Weighted Market returns (RM)* for the full sample, *BFC*, *FC*, and *AFC* periods. The Mean is the average value during the sample and three sub-periods; The Std. dev is the standard deviation; The Min and Max are the minimum and maximum return dispersions, respectively. The whole sample period is from January 1, 2003 to December 31, 2018, the *BFC* period is from January 1, 2003, to June 30, 2007, the *FC* period is from July 1, 2007 to December 31, 2008, and the *AFC* period is from January 1, 2009 to December 31, 2018."

4.2 Herding towards the Chinese Stock Market.

The study starts first with the investigation of herding behavior in the stock markets Shanghai A (S.H.S.A), Shanghai B (S.H.S.B), Shenzhen A (S.Z.S.A), and Shenzhen B (S.Z.S.B) for the full sample period and three sub-periods. Table 2 summarizes the analytical findings. Panel A displays the approximate results using the dummy variable method, with β_1 and β_2 are dummy variables to measure herding in extremely "upper and lower tails of the distribution". This study chooses 1% and 5% criterion levels of D_t^U and D_t^L according to the arbitrary definition of extreme market conditions suggested by (Christie & Huang, 1995). In the entire sample duration for whole markets, the estimates of β_1 and β_2 for CSAD in both criterion levels are statistically positive, indicating that stock return dispersion appears to increase during times of intense price movement, which does not support the occurrence of herding in the Chinese stock market. When the entire sample is divided into sub-periods, however, only the FC periods display signs of herding, suggesting that investors' investment behavior can alter drastically during times of market turbulence.

The estimates of β_1 and β_2 for CSAD for Shanghai A (S.H.S.A) under 1% criterion level, are both negative and statistically significant indicating that herding is observed during up and low 1% extreme price movements, while under 5% criterion level, herding is present only during up 5% extreme price movements. For Shanghai B (S.H.S.B), the estimates of β_1 and β_2 for CSAD are only negative and significant under up 1% criterion level and statistically positive during down extreme market conditions, implying that herding is more pronounced during up extreme price movements, while under 5% criterion, herding is not observed in both periods. The estimates of β_1 and β_2 for CSAD for Shenzhen A (S.Z.S.A), under 1% criterion level, are both negative and statistically significant which indicates that herding is observed during up and low 1% extreme price movements, while under 5% criterion level, herding is present only during up 5% extreme price movements. For Shanghai B (S.H.S.B), the estimates of β_1 and β_2 for CSAD under 1% and 5% criterion level are both positive during up and down market extreme conditions, suggesting that during times of intense price movement, stock return dispersion appears to increase, refuting the notion of herding in the Chinese stock market during the financial crisis.

Besides, this study tests the non-linearity and the results are summarized in panel B of Table 2. Coefficients that are statistically significant and positive. The linear relationship between return dispersions and market returns is suggested by β_1, which is consistent with classical financial theory, which implies that the relationship between return dispersions and market returns is linear under rational asset pricing models. To test nonlinearity, (Chang et al., 2000) added the quadratic term $R_{m,t}$ to the regression model; thus, a statistically negative and significant β_2 indicates the incidence of herding. The empirical results show that the quadratic non-linearity between return dispersion and market returns computed by CSAD is significantly negative for the whole stock markets in China. This discovery provides empirical proof of herding magnitude in the Chinese Stock Market from 2003 to 2018, as well as overall sub-periods such as BFC, FC and AFC. This inference is backed by recent research on the occurrence of herding activity in emerging markets (Dang & Lin, 2016); (Vo & Phan, 2017).

Table 1: The regression Results of *CSAD*.

		Full Sample Period	*BFC* Period	*FC* Period	*AFC* Period
		CSAD	*CSAD*	*CSAD*	*CSAD*
		Panel A: The Dummy Variable Approach			
		1% Criterion Level			
S.H.S.A	$\boldsymbol{\beta_0}$	0.3269***	0.3139***	0.2613***	0.3349***
		368.166	154.697	81.964	330.458
	$\boldsymbol{\beta_1}$	0.0797***	0.2582***	**-0.4905*** **	0.1634***
		11.863	12.597	-47.175	19.270
	$\boldsymbol{\beta_2}$	0.4507***	0.8250***	**-0.0687*** **	0.5015***
		50.591	41.988	-4.139	41.906
	Adj-R²	0.001	0.003	0.001	0.001

S.H.S.B	β_0	0.3580***	0.3399***	0.3120***	0.3588***
		105.910	58.256	33.387	79.698
	β_1	0.4145***	0.3698**	**-0.1816*** **	0.3511***
		6.967	2.260	-3.316	8.457
	β_2	0.6404***	0.9448***	-0.0606	0.7874***
		16.488	13.042	-1.043	13.190
	Adj-R^2	0.004	0.007	0.000	0.004
S.Z.S.A	β_0	0.3254***	0.3122***	0.3230***	0.3244***
		244.624	105.332	45.977	226.924
	β_1	0.1189***	0.2310***	**-0.4910*** **	0.2317***
		10.623	5.808	-7.480	27.297
	β_2	0.2751***	0.7852***	**-0.1770*** **	0.2944***
		24.737	17.924	-6.764	27.109
	Adj-R^2	0.000	0.002	0.000	0.000
S.Z.S.B	β_0	0.3235***	0.2925***	0.2741***	0.3340***
		111.675	60.858	33.224	85.106
	β_1	0.4831***	0.4856***	-0.0029	0.4074***
		14.348	9.272	-0.057	8.530
	β_2	0.6158	0.4605***	0.1892***	0.8098***
		19.397***	8.404	3.011	16.530
	Adj-R^2	0.005	0.005	0.000	0.006
			5% Criterion Level		
S.H.S.A	β_0	0.2954***	0.2839***	0.2606***	0.3058***
		323.995	135.398	76.872	293.503
	β_1	0.1515***	0.2281***	**-0.2281*** **	0.1298***
		45.658	25.857	-31.639	32.669
	β_2	0.5866***	0.5858***	0.1064***	0.5852***
		131.634	67.003	11.438	119.296
	Adj-R^2	0.008	0.007	0.001	0.009
S.H.S.B	β_0	0.3099***	0.2856***	0.2969***	0.3100***
		92.522	50.044	30.599	69.370
	β_1	0.5072***	0.6120***	0.0094	0.5193***
		26.325	14.476	0.277	23.086
	β_2	0.6735***	0.7451***	0.2339***	0.6773***
		37.406	23.126	6.118	28.485
	Adj-R^2	0.020	0.029	0.002	0.019
S.Z.S.A	β_0	0.2959***	0.2815***	0.3266***	0.2965***
		221.076	96.014	43.046	199.537
	β_1	0.1532***	0.1988***	**-0.2553*** **	0.1691***
		24.466	13.596	14.027	25.056
	β_2	0.5134***	0.6129	0.0385***	0.4953***
		64.841	28.673***	2.492	103.084
	Adj-R^2	0.003	0.005	0.000	0.003
S.Z.S.B	β_0	0.2876***	0.2606***	0.2623***	0.2982***
		99.550	54.557	30.756	76.018
	β_1	0.4553***	0.4667***	0.0842**	0.4101***
		30.648	18.877	2.535	20.231
	β_2	0.4756***	0.3669***	0.1840***	0.5524***
		32.988	14.436	5.669	26.017
	Adj-R^2	0.016	0.016	0.002	0.016

		Panel B: The Non-linear Approach			
		CSAD	*CSAD*	*CSAD*	*CSAD*
S.H.S.A	β_0	0.2998***	0.2865***	0.2618***	0.3093***
		329.125	136.476	85.236	295.957
	β_1	0.2058***	0.1946***	0.0359***	0.1722***
		105.484	42.256	3.512	79.199
	β_2	**-0.0300*** **	**-0.0097*** **	**-0.0209*** **	**-0.0196*** **
		-43.807	-4.856	-4.773	-27.316

	Adj-R²	0.008	0.008	0.000	0.008
S.H.S.B	$\boldsymbol{\beta_0}$	0.2949***	0.2810***	0.3021***	0.2987***
		90.091	47.650	30.272	68.080
	$\boldsymbol{\beta_1}$	0.3997***	0.3826***	0.2271***	0.3700***
		37.599	14.189	8.136	45.726
	$\boldsymbol{\beta_2}$	**-0.0624***	**-0.0569***	**-0.0757***	**-0.0535***
		-17.495	-5.356	-6.399	-28.238
	Adj-R²	0.038	0.044	0.005	0.033
S.Z.S.A	$\boldsymbol{\beta_0}$	0.3028***	0.2834***	0.3290***	0.3024***
		226.699	91.215	42.214	208.055
	$\boldsymbol{\beta_1}$	0.2133***	0.2103***	0.0582**	0.1909***
		62.436	22.087	2.322	57.040
	$\boldsymbol{\beta_2}$	**-0.0383***	**-0.0143***	**-0.0398***	**-0.0307***
		-32.086	-2.769	-3.342	-28.607
	Adj-R²	0.003	0.006	0.000	0.003
S.Z.S.B	$\boldsymbol{\beta_0}$	0.2817***	0.2543***	0.2608***	0.2919***
		99.766	54.089	29.884	75.746
	$\boldsymbol{\beta_1}$	0.2919***	0.2482***	0.1783***	0.2668***
		48.989	23.459	8.415	35.336
	$\boldsymbol{\beta_2}$	**-0.0448***	**-0.0359***	**-0.0484***	**-0.0357***
		-24.327	-9.505	-5.513	-17.001
	Adj-R²	0.029	0.026	0.006	0.024

"Notes: Panel A of this table reports the estimation results of dummy variable approach for the full sample, *BFC*, *FC*, and *AFC* periods, which is as follows: $\boldsymbol{CSAD_t = \beta_0 + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t}$, where $\boldsymbol{CSAD_t}$ is the dependent variables in the regression. The independent variables of $\boldsymbol{D_t^U}$ and $\boldsymbol{D_t^L}$ are dummy variables. $\boldsymbol{D_t^U} = 1$ if the market return is in the extreme upper tail of return distribution, 0 otherwise; $\boldsymbol{D_t^L} = 1$ if the market return is in the extreme lower tail of return distribution, 0 otherwise. The criterion for extreme is at *1%* and *5%* of the market returns observations. Panel B of this table reports the estimation results of the non-linear model which is as follow: $\boldsymbol{CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t}$, where $|\boldsymbol{R_{m,t}}|$ is absolute value of the average return of market portfolio on day t, and $\boldsymbol{R_{m,t}^2}$ is the squared value. **BOLD** values imply the occurrence of herding. T-statistics is in parentheses and is corrected for heteroskedasticity and autocorrelation by (Newey & West, 1987). ***, **, and * denote significant level at the *1%*, *5%* and *10%* level, respectively."

4.3 The Effect of Idiosyncratic Volatility.

The sample is divided into three main classes, each representing the degree of idiosyncratic volatility to analyze if herding behavior follows different trends at different levels of idiosyncratic volatility over different sub-periods. Stock portfolios in Group 1 have the lowest idiosyncratic volatility, while stock portfolios in Group 3 have the highest idiosyncratic volatility, and stock portfolios in Group 2 includes the rest. This research uses the CSAD approach to detect herding activity in three portfolios over three sub-periods, sorting by individual stock idiosyncratic volatility. Table 3 summarizes the predicted outcomes. Table 3's Panel A displays the findings under extreme conditions.

The results show that during the full sample period the coefficients β_1 and β_2 are all positive in Shanghai A (S.H.S.A) for most cases according to the two criterion levels. While Shanghai B (S.H.S.B), herding is observed under 1% criterion level, during both extreme market conditions and within stock portfolios with the smallest idiosyncratic volatility. For Shenzhen A (S.Z.S.A), herding is noticeable under the 1% criterion level, during both extreme market condition and within stock portfolios with medium idiosyncratic volatility, while in Shenzhen B (S.Z.S.B), herding is only present during periods of low extreme price movements under 1% criterion level within stock portfolios with smallest idiosyncratic volatility. During the BFC period, only Shanghai B (S.H.S.B) exhibited herding behavior under the 1% criterion level during periods of upper extreme price movement within stock portfolios with medium idiosyncratic volatility and during periods of lower extreme price movements within largest idiosyncratic volatility stock portfolios. Most estimated coefficients of group 3 and group 2 are statistically negative during the FC phase, suggesting the existence of herding. The findings suggest that the financial crisis of 2007–2008 exacerbated herding, especially in stock portfolios with the highest idiosyncratic volatility. More particularly, in Shanghai A (S.H.S.A) and Shanghai B (S.H.S.B), herding is evidenced under a 1% criterion level during both extreme market conditions within the smallest idiosyncratic volatility stock portfolios and during up extreme market conditions within the largest idiosyncratic volatility stock portfolios . While, under the 5% criterion level, herding is pronounced only during both extreme market conditions within the largest idiosyncratic volatility stock portfolios.

For Shenzhen A (S.Z.S.A), herding is observed during upper extreme market conditions within stock portfolios with smallest idiosyncratic volatility under both criterion levels and also during both extreme market conditions within stock portfolios with medium idiosyncratic volatility under 1% criterion level, while only during upper extreme market conditions under 5% criterion level, as well as during both market extreme conditions within stock portfolios with largest idiosyncratic volatility under 5% criterion level. Finally, for Shenzhen B (S.Z.S.B), herding is only evidenced within stock portfolios with the largest idiosyncratic volatility, during both extreme market conditions under 1% criterion level while only during down extreme market conditions under 5% criterion level. During the AFC period, only Shanghai B (S.H.S.B) and Shenzhen A (S.Z.S.A) exhibited herding behavior. More particularly, in Shanghai B (S.H.S.B), herding is observed within stock portfolios with the smallest idiosyncratic volatility, during both extreme market conditions under 1% criterion level and during down extreme market conditions under 5% criterion level. For Shenzhen A (S.Z.S.A), herding is observed within stock portfolios with medium idiosyncratic volatility, during both extreme market conditions under 1% criterion level and during down extreme market conditions under 5% criterion level. Also, herding is observed within stock portfolios with the largest idiosyncratic volatility, during down extreme market conditions under the 1% criterion level. Overall, the empirical results suggest that the financial crisis of 2007–2008 encouraged herding, especially in portfolios with medium to high idiosyncratic volatility.

The results of the non-linear regression used to estimate herding strength within different classes of idiosyncratic volatility are shown in Panel B. To analyze herding under sub-periods under different levels of idiosyncratic instability, the sample is divided into three sub-periods: BFC, FC and AFC. The bulk of β_2 coefficients are strongly negative, according to the empirical findings. This result reveals the existence of a non-linear model over time and through groups. The supportive occurrence of herding is consistent with Table 2's findings. With the exception of Shanghai A (S.H.S.A) within the smallest idiosyncratic volatility stock portfolios, all markets demonstrated herding within three ranges of idiosyncratic volatility throughout the entire sample span. Herding is more pronounced in Shanghai A (S.H.S.A) and Shenzhen A (S.Z.S.A) with the highest idiosyncratic volatility stock portfolios than the lowest idiosyncratic volatility stock portfolios during the BFC period.

While Shanghai B (S.H.S.B), herding is observed more within stock portfolios with medium idiosyncratic volatility than smallest idiosyncratic volatility. Similarly, herding in Shenzhen B (S.Z.S.B) is observed within three levels of idiosyncratic volatility and more intense within the largest idiosyncratic volatility stock portfolios. During the FC period, herding is evidenced in Shanghai A (S.H.S.A) and Shanghai B (S.H.S.B) only within the largest idiosyncratic volatility stock portfolios. While, Shenzhen A (S.Z.S.A) within medium idiosyncratic volatility stock portfolios and Shenzhen B (S.Z.S.B) within stock portfolios with medium and largest idiosyncratic volatility, with herding more pronounced within the latter. AFC period, herding is evidenced in Shanghai B (S.H.S.B) and Shenzhen A (S.Z.S.A) within three levels of idiosyncratic volatility, however, herding is more intense with the largest idiosyncratic volatility stock portfolios. In Shanghai A (S.H.S.A), herding is only observed in the largest idiosyncratic volatility stock portfolios, while Shenzhen B (S.Z.S.B), herding is more pronounced with medium idiosyncratic volatility stock portfolio than the smallest idiosyncratic volatility stock portfolios.

Furthermore, the major disparity between groups 3 and 1 supports herding in stock portfolios with higher idiosyncratic volatility. For example, the test difference shows that stock portfolios with higher idiosyncratic volatility promote herding in the overall markets over the entire sample period. During the BFC time, however, only a small amount of evidence was found in Shenzhen B (S.Z.S.B). During the FC time, the test difference between groups 3 and 1 serves as a secondary indicator of herding in high idiosyncratic volatility stock portfolios, especially in Shanghai A (S.H.S.A), Shanghai B (S.H.S.B), and weak evidence in Shenzhen B (S.Z.S.B), implying that initiative-based trade behavior is usually apparent during FC periods. During the AFC period, only Shanghai A (S.H.S.A), Shanghai B (S.H.S.B) where investors significantly tend to herd in larger idiosyncratic volatility stock portfolios, while with a small magnitude in Shenzhen A (S.Z.S.A).

When the coefficients are compared across the groups with idiosyncratic volatility, it is clear that the higher idiosyncratic volatility stock portfolios and a higher herding level supports the presence of style investors. These findings also indicate that when undiversified investors follow the strategies of other investors, idiosyncratic volatility can have a significant effect on herd conduct. The empirical results are consistent with those of (Chang & Dong, 2006) who used Japanese data from 1975 to 2003 to investigate the relationship between institutional herding and firm idiosyncratic volatility. Their findings show a clear correlation between institutional herding and high idiosyncratic volatility. The results, on the other hand, contradict the findings of (Vo & Phan, 2019a), who say that during the global financial crisis, many individual investors restricted their trading of stocks with high idiosyncratic volatility due to their “loss-averse sentiment”.

Table 2 : The Regression Results of *CSAD* Within the Stock Portfolios of Idiosyncratic Volatility.

		Panel A: The Dummy Variable Approach								Panel B: The Non-linear Approach			
		1% Criterion Level				*5%* Criterion Level							
		β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2
Markets													
						Full Sample Period							
S.H.S.A	Group1	0.0264***	0.0947***	0.0368***	0.000	0.0243	0.0350	0.0320	0.000	0.0224***	0.0186***	0.0003	0.001
		45.307	17.074	6.557		40.039	13.467	12.314		37.470	15.910	0.971	
	Group2	0.0529***	0.0483***	0.1053***	0.000	0.0443***	0.0751***	0.1279***	0.002	0.0457***	0.0826***	**-0.0162*** **	0.005
		75.308	7.919	17.966		60.399	27.099	46.001		63.044	58.538	-36.362	
	Group3	0.3685***	-0.0007	0.0361**	0.000	0.3500***	0.1162***	0.2567***	0.001	0.3508***	0.1670***	**-0.0355*** **	0.002
		191.629	-0.058	2.346		173.745	18.513	30.240		172.572	33.993	-18.363	
	G3-G1		-0,0954***	-0,0007			0,0812***	0,2247***			0,1484***	-0,0358***	
			-7,1106962	-0,04			12,10	26,30			29,10	-17,90	
S.H.S.B	Group1	0.0258***	**-0.1254*** **	**-0.0977*** **	0.001	0.0229***	0.0093	0.0025	0.000	0.0213***	0.0567***	**-0.0130*** **	0.005
		10.535	-4.910	-3.724		8.980	0.818	0.219		8.407	14.440	17.838	
	Group2	0.0525***	0.1299***	0.2391***	0.002	0.0447***	0.0940***	0.1307***	0.003	0.0410***	0.0672***	**-0.0076*** **	0.007
		20.724	6.030	9.326		16.948	8.512	11.297		15.769	14.858	-7.453	
	Group3	0.4073***	0.2060	-0.0325	0.000	0.3825***	0.2642***	0.2641***	0.004	0.3832***	0.2332***	**-0.0498*** **	0.009
		70.655	1.559	-0.524		64.483	7.841	10.085		57.345	7.838	-3.732	
	G3-G1		0,3314***	0,0652			0,2549***	0,2616***			0,1765***	-0,0368**	
			2,4633	0,9698			7,1330	9,1355			5,8317	-2,8224	
S.Z.S.A	Group1	0.0423***	0.0083	0.0375***	0.000	0.0386***	0.0552***	0.0281***	0.000	0.0406***	0.0671***	**-0.0184*** **	0.002
		67.650	1.223	5.634		59.644	18.236	9.643		63.478	49.745	-41.915	
	Group2	0.0725***	**-0.0167** **	**-0.2704*** **	0.002	0.0627***	0.1124***	0.0241***	0.001	0.0713***	0.1406***	**-0.0456*** **	0.008
		95.110	-2.218	-36.346		79.631	34.432	7.142		91.315	87.106	-83.420	
	Group3	0.3883***	0.0686***	-0.0357	0.000	0.3716***	0.0950***	0.2439***	0.000	0.3768***	0.1658***	**-0.0408*** **	0.001
		118.319	2.598	-1.401		111.286	6.255	13.105		108.365	16.963	-10.241	
	G3-G1		0,0603**	-0,0732**			0,0398**	0,2158***			0,0987***	-0,0224***	

			2,23949	-2,81956			2,60181	11,21891			9,82102	-5,60000	
S.Z.S.B	Group1	0.0161***	-0.0291	**-0.0569****	0.000	0.0152***	-0.0001	0.0026	0.000	0.0135***	0.0377***	**-0.0094*****	0.002
		6.732	-1.235	-2.453		6.061	-0.013	0.243		5.417	9.274	-10.041	
	Group2	0.0587***	0.1126***	0.1059***	0.001	0.0527***	0.0852***	0.0800***	0.002	0.0509***	0.0561***	**-0.0083*****	0.004
		23.215	4.755	4.281		20.016	7.531	7.033		19.491	11.610	-6.360	
	Group3	0.3527***	0.1684***	0.1700***	0.000	0.3310***	0.2806***	0.2153***	0.005	0.3333***	0.1415***	**-0.0244*****	0.006
		73.027	3.497	3.287		67.183	12.507	10.059		66.884	11.045	-4.737	
	G3-G1		1,4034***	2,6230***			0,2807***	0,2127***			0,1038***	-0,0150***	
			26,1508	46,1313			11,4121	8,9722			7,6315	-2,9417	
							BFC Period						
S.H.S.A	Group1	0.0296***	0.0254**	0.0365***	0.000	0.0286***	0.0078	0.0256***	0.000	0.0283***	0.0225***	**-0.0050*****	0.000
		24.245	2.230	2.933		22.445	1.422	4.598		22.124	6.860	-3.461	
	Group2	0.0480***	0.0262**	0.3103***	0.003	0.0441***	0.0126**	0.1350***	0.002	0.0398***	0.0053*	0.0162***	0.004
		37.208	2.170	25.902		32.880	2.220	23.132		30.146	1.814	15.689	
	Group3	0.3870***	0.1314***	0.1597***	0.000	0.3640***	0.1530***	0.3547***	0.001	0.3716***	0.1135***	**-0.0103****	0.001
		82.651	3.019	4.366		73.817	7.984	21.761		73.975	10.266	-2.081	
	G3-G1		0,1060**	0,1232***			0,1452***	0,3291***			0,0910***	-0,0053	
			2,3372	3,1673			7,3905	19,2591			7,9812	-1,0394	
S.H.S.B	Group1	0.0284***	0.0055	-0.0072	0.000	0.0260***	0.0242	0.0227	0.000	0.0257***	0.0359***	**-0.0076*****	0.001
		6.058	0.121	-0.163		5.311	1.171	1.065		5.305	3.723	-2.792	
	Group2	0.0485***	**-0.1083*****	0.2705***	0.002	0.0407***	0.0295	0.1571***	0.003	0.0403***	0.0720***	**-0.0120*****	0.005
		10.034	-5.303	5.822		8.061	1.505	7.231		8.120	7.984	-5.828	
	Group3	0.3826***	0.4070	**-0.1639*****	0.001	0.3571***	0.2449***	0.3072***	0.005	0.3581***	0.2429***	-0.0491	0.012
		39.642	1.219	-1.880		36.166	2.985	6.216		25.408	3.280	-1.362	
	G3-G1		0,4015	-0,1567			0,2207**	0,2845***			0,2070**	-0,0415	
			1,1913	-1,6073			2,6073	5,3367			2,7721	-1,1488	
S.Z.S.A	Group1	0.0354***	-0.0071	0.0679***	0.000	0.0350***	-0.0103	0.0305***	0.000	0.0343***	21.160***	**-0.0055*****	0.000
		22.983	-0.498	3.863		21.812	-1.510	4.216		0.0223	5.148	-2.679	
	Group2	0.0464***	0.0060	0.3610***	0.003	0.0424***	0.0163**	0.1337***	0.002	0.0364***	-0.0056	0.0217***	0.005
		28.241	0.368	19.477		24.841	2.277	17.508		21.561	-1.476	14.950	

	Group3	0.3863***	0.1287	0.1492	0.000	0.3624***	0.1398***	0.3873***	0.001	0.3725***	0.1427***	**-0.0225***	0.001
		54.222	1.216	1.395		48.665	3.829	11.710		46.498	6.349	-1.733	
	G3-G1		0,1358	0,0813			0,1501***	0,3568***			-21,0173	-0,0170	
			1,2701	0,7493			4,0928	10,5768			-939,9222	-1,2925	
S.Z.S.B	Group1	0.0327***	0.0390	-0.0727	0.000	0.0297***	0.0372**	0.0160	0.000	0.0304***	0.0336***	**-0.0091****	0.001
		7.368	0.933	-1.620		6.431	1.852	0.780		6.555	3.056	-2.230	
	Group2	0.0506***	0.1386***	0.0590	0.001	0.0459***	0.0746***	0.0589***	0.001	0.0439***	0.0543***	**-0.0094*****	0.003
		10.961	3.400	1.390		9.575	3.656	2.826		9.250	6.057	-3.758	
	Group3	0.3257***	0.1404	0.1808**	0.001	0.3008***	0.2940***	0.2627***	0.007	0.3116***	0.1824***	**-0.0367*****	0.010
		40.171	1.541	2.030		36.804	7.886	6.094		37.010	8.375	-3.948	
	G3-G1		0,1014	0,2535**			0,2568***	0,2467***			0,1488***	-0,0276**	
			1,0117	2,5419			6,1056	5,1553			6,0496	-2,8024	
							FC Period						
S.H.S.A	Group1	0.0282***	0.0356***	0.1399***	0.001	0.0281***	-0.0024	0.0462***	0.000	0.0263***	-0.0120*	0.0096***	0.000
		13.025	3.794	6.327		12.529	-0.284	4.684		11.322	-1.871	3.293	
	Group2	0.0483	**-0.6416*****	**-0.4207*****	0.005	0.0365***	-0.0420***	0.1601***	0.003	0.0357***	-0.0184***	0.0165***	0.001
		22.521	-5.945	-43.077		16.407	-3.666	16.905		14.753	-2.583	4.668	
	Group3	0.3354***	**-0.3915*****	0.0359	0.000	0.3530***	**-0.1872*****	**-0.2223*****	0.001	0.3509***	0.0125	**-0.0367****	0.000
		40.028	-17.104	0.878		39.030	-13.422	-11.047		46.256	0.392	-2.422	
	G3-G1		-0,4271***	-0,1040**			-0,1848***	-0,2685***			0,0245	-0,0463***	
			-17,29	-2,24			-11,10	-12,01			0,75	-3,03	
S.H.S.B	Group1	0.0185**	0.6561***	0.1666*	0.012	0.0197**	0.1196***	0.0165	0.002	0.0081	-0.0716***	0.0480***	0.007
		2.261	11.156	1.910		2.309	3.156	0.441		0.929	-2.776	4.568	
	Group2	0.0417***	**-0.2256*****	**-0.0689***	0.002	0.0325***	-0.0440	0.1619***	0.004	0.0334***	0.0187	-0.0015	0.000
		4.884	-3.159	-1.944		3.664	-1.167	4.518		3.674	0.668	-0.132	
	Group3	0.3465***	**-0.1741****	-0.0857	0.000	0.3583***	**-0.1390*****	**-0.1408*****	0.002	0.3627***	0.0979*	**-0.0665****	0.001
		22.964	-2.198	-1.041		22.421	3.088	-2.616		21.616	1.851	-2.521	
	G3-G1		-0,8302***	-0,2523**			-0,2586***	-0,1573**			0,1695**	-0,1145***	
			-8,4199	-2,1104			-4,3906	-2,4030			2,8712	-4,0558	
S.Z.S.A	Group1	0.0544***	**-0.1730*****	0.3119***	0.003	0.0529***	**-0.0423*****	0.0965***	0.001	0.0553***	0.0110	-0.0039	0.000

		20.571	-12.763	8.356		19.438	-3.966	6.633		19.692	1.346	-1.005	
	Group2	0.0336***	**-1.2026*** **	**-0.5133*** **	0.008	0.0277***	**-0.1100*** **	0.0693***	0.001	0.0344***	0.0263***	**-0.0188*** **	0.000
		12.142	-13.707	-45.171		9.698	-7.667	5.809		11.173	2.938	-4.204	
	Group3	0.4443***	-0.2900	-0.0636	0.000	0.4695	**-0.2134*** **	**-0.3231*** **	0.000	0.4645***	-0.0416	-0.0210	0.000
		22.494	-1.376	-0.706		21.933	-3.270	-9.204		20.053	-0.511	-0.475	
	G3-G1		-0,1170	-0,3755***			-0,1711**	-0,4196***			-0,0526	-0,0171	
			-0,5533	-3,8588			-2,5954	-11,0192			-0,6462	-0,3870	
S.Z.S.B	Group1	0.0236	0.2553	0.0814	0.002	0.0253***	0.0736*	-0.0345	0.001	0.0181***	-0.0095	0.0122	0.001
		3.049	2.978	1.043		3.145	1.897	-0.983		2.200	-0.431	1.352	
	Group2	0.0408***	-0.0871	0.4752***	0.006	0.0354***	0.0038	0.1774***	0.004	0.0347***	0.0824***	**-0.0195** **	0.004
		5.034	-1.285	6.835		4.187	0.107	4.891		4.020	3.524	-1.989	
	Group3	0.3446***	**-0.2841*** **	**-0.2922*** **	0.002	0.3431***	0.0312	**-0.1340** **	0.001	0.3569***	0.0599	**-0.0515** **	0.001
		23.042	-4.524	-3.068		22.187	0.552	-2.465		21.862	1.230	-2.171	
	G3-G1		-0,5394***	-0,3736***			-0,0424	-0,0995			0,0694	-0,0637**	
			-5,0597	-5,0267			-0,6139	-1,5462			1,2921	-2,4852	
							AFC Period						
S.H.S.A	Group1	0.0244***	0.0816***	0.0556***	0.000	0.0227***	0.0348***	0.0251***	0.000	0.0209***	0.0158***	0.0007**	0.001
		34.593	12.365	8.252		30.940	11.187	7.954		29.068	11.917	2.078	
	Group2	0.0244***	0.0816***	0.0556***	0.000	0.0227***	0.0348***	0.0251***	0.000	0.0209***	0.0158***	0.0007**	0.001
		34.593	12.365	8.252		30.940	11.187	7.954		29.068	11.917	2.078	
	Group3	0.3849***	0.0905***	0.1383***	0.000	0.3658***	0.0925***	0.3320***	0.002	0.3626***	0.1230***	**-0.0144*** **	0.003
		186.837	5.856	6.435		168.566	14.244	38.627		164.835	22.327	-6.786	
	G3-G1		0,0089	0,0827***			0,0577***	0,3069***			0,1072***	-0,0151***	
			0,5377	3,7360			8,6014	32,3501			17,6236	-7,5500	
S.H.S.B	Group1	0.0301***	**-0.1755*** **	**-0.1801*** **	0.002	0.0275***	0.0120	**-0.0314** **	0.000	0.0256***	0.0509***	**-0.0112*** **	0.008
		9.626	-5.290	-5.557		8.444	0.801	-2.176		7.884	11.491	-18.701	
	Group2	0.0565***	0.1064***	0.1179***	0.001	0.0506***	0.0872***	0.0735***	0.002	0.0469***	0.0642***	**-0.0090*** **	0.005
		17.220	3.269	3.364		14.862	5.932	4.833		13.948	10.704	-5.908	
	Group3	0.4324***	-0.0429	0.2068	0.000	0.4003***	0.2686***	0.4041***	0.005	0.4037***	0.2061***	**-0.0361*** **	0.007
		52.559	-0.860	2.199		47.587	7.857	10.175		47.318	10.568	-5.658	

	G3-G1		0,1326*	0,3869***			0,2566***	0,4355***			0,1552***	-0,0249***	
			2,2134	3,8964			6,9049	10,2763			7,6093	-4,0935	
S.Z.S.A	Group1	0.0322***	0.0865***	0.0382***	0.000	0.0276***	0.0978***	0.0197***	0.001	0.0305***	0.0771***	**-0.0201*** **	0.003
		46.613	10.106	4.815		38.625	27.379	5.978		43.159	51.105	-39.129	
	Group2	0.0557***	**-0.0312*** **	**-0.4857*** **	0.006	0.0480***	0.1051***	**-0.0576*** **	0.002	0.0580***	0.1369***	**-0.0504*** **	0.012
		70.934	-3.369	-61.437		59.189	27.971	-15.218		72.276	82.306	-95.559	
	Group3	0.3934***	0.1201***	**-0.0710*** **	0.000	0.3769***	0.0855***	0.2501***	0.000	0.3797***	0.1339***	**-0.0292*** **	0.001
		113.947	8.010	-3.260		103.955	5.164	28.890		103.757	14.130	-8.257	
	G3-G1		0,0336*	-0,1092***			-0,0123	0,2304***			0,0568***	-0,0091*	
			1,9208	-4,6648			-0,7043	24,2863			6,1608	-2,2071	
S.Z.S.B	Group1	0.0228	-0.0313	-0.0479	0.000	0.0213***	0.0015	0.0112	0.000	0.0186***	0.0366***	**-0.0072*** **	0.002
		7.254	-0.969	-1.619		6.516	0.101	0.803		5.737	8.194	-9.398	
	Group2	0.0591***	0.1192***	0.0744**	0.001	0.0531***	0.0938***	0.0637***	0.002	0.0522***	0.0580***	**-0.0094*** **	0.003
		17.689	3.538	2.457		15.253	6.354	4.284		15.211	10.536	-7.310	
	Group3	0.3769***	0.3489***	0.4458***	0.003	0.3578***	0.2573***	0.2953***	0.005	0.3534***	0.0844***	0.0039	0.006
		55.325	4.617	6.569		51.206	7.861	9.579		50.294	4.706	0.561	
	G3-G1		0,3802***	0,4937***			0,2558***	0,2841***			0,0478**	0,0111	
			4,6106	6,6426			7,1359	8,3523			2,5923	1,5698	

"**Notes:** Panel A of this table reports the estimation results of the dummy variable approach for the full sample, *BFC*, *FC*, and *AFC* periods, which is as follow: $\boldsymbol{CSAD_t = \beta_0 + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t}$, where $\boldsymbol{CSAD_t}$ is the dependent variables in the regression. The independent variables of $\boldsymbol{D_t^U}$ and $\boldsymbol{D_t^L}$ are dummy variables. $\boldsymbol{D_t^U}$ = 1 if the market return is in the extreme upper tail of return distribution, 0 otherwise; $\boldsymbol{D_t^L}$ = 1 if the market return is in the extreme lower tail of return distribution, 0 otherwise. The criterion for extreme is at *1%* and *5%* of the market returns observations. Panel B of this table reports the estimation results of the non-linear model, which is as follow: $\boldsymbol{CSAD_t = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t}$, where $\boldsymbol{|R_{m,t}|}$ is absolute value of the average return of market portfolio on day t, and $\boldsymbol{R_{m,t}^2}$ is the squared value. **BOLD** values imply the occurrence of herding. T-statistics is in parentheses and is corrected for heteroskedasticity and autocorrelation by (Newey & West, 1987). ***, **, and * denote significant level at the *1%*, *5%* and *10%* level, respectively."

4.4 Asymmetric Effect of Idiosyncratic Volatility on Herding Behavior during Rising and Falling Markets.

The analysis then looks at the asymmetric impact of herding in “up and down markets” with varying levels of idiosyncratic volatility over three sub-periods and the entire sample period. The findings are shown in Tables 4 and 5. Table 4 shows the results in down markets, while Table 5 shows the results in up markets.”

Except in a few situations, the majority of the β_2 herding coefficients are substantially negative in four cycles inside three classes of idiosyncratic volatility. More precisely, the majority of quadratic term coefficients are found to be negative and important across the entire study, meaning that there is no evidence to support the predictions of rational capital asset pricing models like “CAPM or APT.” The empirical evidence of the decrease in dispersion of returns in rising and falling market confirms the homogeneous trading behavior, except in Shanghai A (S.H.S.A) within smallest idiosyncratic volatility stock portfolios and in Shanghai B (S.H.S.B) with largest idiosyncratic volatility stock portfolios during rising markets in the whole sample period.

In the BFC period and during falling markets, there is exist a little evidence of herding in Shanghai A (S.H.S.A) with smallest and largest idiosyncratic volatility stock portfolios, while during rising markets there exist significant evidence of herding within stock portfolios s with smallest and largest idiosyncratic volatility. For Shanghai B (S.H.S.B), herding is significant within stock portfolios with smallest and largest idiosyncratic volatility during falling markets, while during rising markets, only significant proof of herd conduct within medium idiosyncratic volatility stock portfolios. For Shenzhen A (S.Z.S.A), herding is only evidenced within the largest idiosyncratic volatility within stock portfolios during falling markets, and only within stock portfolios with the smallest idiosyncratic volatility during rising markets. Finally, little evidence of herding within stock portfolios s with the smallest and largest idiosyncratic volatility in Shenzhen B (S.Z.S.B) during falling markets, while little proof of herd conduct within medium idiosyncratic volatility stock portfolios, and significant proof within largest idiosyncratic volatility stock portfolios during rising markets.

In the FC period, herding is more evidenced almost within stock portfolios with medium and largest idiosyncratic volatility. During falling markets, herding is exhibited in Shanghai A (S.H.S.A) within stock portfolios with medium and largest idiosyncratic volatility while no evidence of herding during rising markets, which reflect the fact that during the global financial crisis, many individual investors limit their trading of stocks with high idiosyncratic volatility due to their sentiment of loss-aversion. In Shanghai B (S.H.S.B), herding is observed with weak evidence within stock portfolios with largest idiosyncratic volatility during falling markets, however little evidence within stock portfolios s with medium and largest idiosyncratic volatility during rising markets. In Shenzhen B (S.Z.S.B), during falling markets, there is poor evidence of herd conduct in the highest idiosyncratic volatility stock portfolios, yet strong evidence of herding in medium idiosyncratic volatility stock portfolios.

In the AFC period, herding is observed almost within three groups and across all markets. More specifically, in Shanghai B (S.H.S.B) and Shenzhen A (S.Z.S.A), herding is evidenced within three groups of idiosyncratic volatility during rising and falling markets. While, in Shanghai A (S.H.S.A), there is significant evidence of herding in both stock portfolios with medium and largest idiosyncratic volatility during falling and rising markets. Similarly, in Shenzhen B (S.Z.S.B) herding is observed in both stock portfolios with smallest and medium idiosyncratic volatility during falling and rising markets. Overall, the findings suggest that idiosyncratic volatility is essential for herding as it may trigger different herding patterns among investors concerning different market trends and its level.

The fact that there was a substantial gap between the two classes for the entire sample period shows that during periods of market downturn, herding in whole markets is more pronounced in stock portfolios with the largest idiosyncratic volatility in the full sample period, suggesting that increase of idiosyncratic volatility is an intensification driven factor of herding behavior. During the BFC period, herding is only observable with a greater magnitude in the largest idiosyncratic volatility stock portfolios in both Shanghai B (S.H.S.B) and Shenzhen A (S.Z.S.A). During the FC period, herding is more noticeable in the largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A) and Shenzhen A (S.Z.S.A) and with weak evidence in Shanghai B (S.H.S.B). During the AFC period, herding is more in the largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A) and Shenzhen A (S.Z.S.A) and in the smallest idiosyncratic volatility stock portfolios in Shanghai B (S.H.S.B).

During the rising market, herding is only pronounced with a greater magnitude in the largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A). During the BFC period, herding is again evidenced in Shanghai A (S.H.S.A) and with a little evidence in Shenzhen B (S.Z.S.B). During the FC period, herding in evidenced only in Shanghai B (S.H.S.B) and with weak evidence in Shenzhen B (S.Z.S.B). During the AFC period, herding is significantly observed in Shanghai B (S.H.S.B) and with weak evidence in Shanghai A (S.H.S.A).

In addition, the t-test is duplicated to compare the herding coefficients of ${\beta_2}^{UP}$ and ${\beta_2}^{DOWN}$under up and down market within three groups is duplicated. The null hypothesis that nonlinearity is the same between up and down markets holds is tested. The results in table 5, imply that herding follow different patterns with regard to the level of idiosyncratic volatility and the period concerned. In Shanghai A (S.H.S.A), herding is more pronounced in largest idiosyncratic volatility stock portfolios during rising markets in the BFC period and AFC period during falling markets. In addition, herding is also noticeable in falling markets during the full sample period and FC period in the smallest idiosyncratic volatility for stock portfolios. Also, herding is pronounced in falling markets in full sample period, FC period, and AFC period for medium idiosyncratic volatility stock portfolios. In Shanghai B (S.H.S.B), herding is only more pronounced in rising markets in the largest idiosyncratic volatility stock portfolios during the AFC period. While, herding is also pronounced falling markets during full sample period and FC period for stock portfolios with smallest idiosyncratic volatility. Also, herding is more noticeable during falling markets in full sample period and rising period during FC period and AFC period for medium idiosyncratic volatility stock portfolios. In Shenzhen A (S.Z.S.A), herding is pronounced in falling markets in full sample period and AFC period for larger idiosyncratic volatility stock portfolios. In addition, herding is also noticeable during rising markets in full sample period, FC period, and AFC period for the smallest idiosyncratic volatility stock portfolios. Also, herding is more apparent during falling markets in the FC period and during rising markets in the AFC period for medium idiosyncratic volatility stock portfolios. In Shenzhen B (S.Z.S.B), no evidence of herding disparity between up and down markets for larger idiosyncratic volatility stock portfolios with during all periods. While, herding is more pronounced during falling markets in full sample period and FC period for stock portfolios with smallest idiosyncratic volatility. In addition, herding is also more apparent during rising markets in the FC period and AFC period for medium idiosyncratic volatility stock portfolios.

The findings in almost all cases suggest that idiosyncratic volatility affects herding behavior by triggering different herding patterns behavior under numerous market conditions and trends. Furthermore, taking into consideration the macro-micro structure of the Chinese framework, the information scarcity, and the dominance of retail investors who are major market participants, one can argue that by the reason of wealth constraints or by the subjective choices, many of these investors do not hold diversified portfolios (Xu & Malkiel, 2003). As a consequence, the more they face the risk of information scarcity, the more the idiosyncratic volatility of their stocks increases and the herding behavior occurs (BenSaïda, 2017). (Bikhchandani et al., 1992) point that non-transparency is one of the primary factors leading to herding.

Table 3 : Herding in Down Markets within Stock Portfolios of Idiosyncratic Volatility.

		Falling market															
		Full Sample Period				*BFC* Period				*FC* Period				*AFC* Period			
Market																	
		β_0	β_1	β_2	Adj-R^2	β_0	1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2
S.H.S.A	Group1	0.0286***	0.0190***	**-0.0022*****	0.001	0.0374***	0.0223***	**-0.0039***	0.000	0.0420	-0.0432***	0.0296	0.001	0.0214***	0.0088***	0.0008	0.001
		30.315	10.443	-4.095		19.334	4.560	-1.828		10.274	-3.661	4.496		18.607	4.398	1.570	
	Group2	0.0661***	0.1022***	**-0.0211*****	0.007	0.0490***	0.0305***	0.0141***	0.011	0.0803	0.0522	**-0.0151*****	0.002	0.0626***	0.0946***	**-0.0203*****	0.006
		59.796	50.423	-36.381		25.295	7.164	11.386		21.785	5.231	-3.187		46.369	42.427	-35.549	
	Group3	0.3571***	0.2041***	**-0.0450*****	0.004	0.3663***	0.1290***	**-0.0103***	0.003	0.3682***	0.1128***	**-0.0793*****	0.001	0.3655***	0.1647***	**-0.0255*****	0.004
		121.492	28.650	-17.633		65.865	8.753	-1.711		49.993	3.391	-5.013		94.610	19.720	-8.934	
	G3-G1		0,1851***	-0,0428***			0,1067***	-0,0064			0,156***	-0,1089***			0,1559***	-0,0263***	
			25,42544	-13,5345			6,748300	-1,01192			4,442659	-6,23559			18,9056	-8,31679	
S.H.S.B	Group1	0.0153	0.0554	**-0.0123*****	0.004	0.0302***	0.0469***	**-0.0121*****	0.001	0.0215*	-0.0322	0.0196	0.001	0.0111***	0.0485***	**-0.0110*****	0.008
		4.082	9.481	-10.876		4.471	3.238	-2.817		1.676	-0.813	1.136		2.283	7.487	-12.418	
	Group2	0.0399***	0.0693***	**-0.0062*****	0.010	0.0395***	0.0792***	-0.0023	0.014	0.0516***	-0.0129	0.0191	0.003	0.0367***	0.0515***	**-0.0060*****	0.004
		10.402	9.849	-3.577		5.640	5.458	-0.566		3.938	-0.336	1.243		7.287	5.993	-3.017	
	Group3	0.3625***	0.2768***	**-0.0646*****	0.010	0.3443***	0.3856***	**-0.1045*****	0.021	0.3364***	0.1208	**-0.0653***	0.001	0.3841***	0.1846***	**-0.0240*****	0.008
		40.441	12.303	-8.152		24.328	10.597	-7.315		14.307	1.598	-1.781		28.010	6.177	-2.566	
	G3-G1		0,2214***	-0,0523***			0,3387***	-0,0924***			0,153	-0,0849*			0,1361***	-0,013	
			9,3143	-6,48701			8,76861	-6,34605			1,78148	-2,085			4,4485	-1,435	
S.Z.S.A	Group1	0.0407***	0.0327***	**-0.0082*****	0.001	0.0476***	0.0132**	0.0006	0.000	0.0693***	-0.0930***	0.0633***	0.003	0.0180***	0.0262***	**-0.0057*****	0.001
		40.261	15.928	-12.153		19.468	1.989	0.189		13.485	-5.757	7.015		16.189	11.942	-7.970	
	Group2	0.0764***	0.1424***	**-0.0464*****	0.010	0.0487***	0.0142***	0.0207***	0.012	0.0921***	0.1113***	**-0.0568*****	0.002	0.0494***	0.1197***	**-0.0464*****	0.016
		63.843	62.052	-65.753		20.080	2.699	12.067		19.879	8.755	-9.564		40.228	51.334	-69.845	
	Group3	0.3872***	0.2158***	**-0.0563*****	0.001	0.3951***	0.2075***	**-0.0426*****	0.001	0.4799***	0.1295	**-0.1055****	0.000	0.3875***	0.1757***	**-0.0416*****	0.002
		87.556	19.133	-14.080		30.213	6.702	-2.613		15.675	1.183	-2.084		87.917	18.610	-12.099	
	G3-G1		0,1831***	-0,0481***			0,1943***	-0,0432***			0,2225*	-0,1688***			0,1495***	-0,0359***	
			16,376	-11,665			6,1138	-2,6537			2,001	-3,2594			16,21	-11,352	
S.Z.S.B	Group1	0.0110***	0.0398***	**-0.0108*****	0.002	0.0341***	0.0375**	**-0.0143***	0.001	0.0124	0.0474	-0.0144	0.001	0.0106**	0.0425***	**-0.0088*****	0.003
		3.008	6.646	-7.586		5.238	2.064	-1.862		1.048	1.485	-1.129		2.147	6.505	-7.674	
	Group2	0.0566***	0.0495***	**-0.0081*****	0.003	0.0493***	0.0476***	**-0.0081****	0.002	0.0323***	-0.0086	0.0312**	0.012	0.0542***	0.0455***	**-0.0067*****	0.003
		14.545	7.104	-4.321		7.260	3.627	-2.235		2.642	-0.270	2.472		10.342	5.977	-4.414	

Group3	0.3314***	0.1457***	**-0.0285*** **	0.006	0.3183***	0.1692***	**-0.0294** **	0.009	0.3417***	0.0702	**-0.0546***	0.002	0.3446****	0.0695***	0.0083	0.009
	46.018	8.207	-4.255		25.574	5.170	-2.034		15.429	1.037	-1.650		33.602	2.926	1.021	
G3-G1		0,1059***	-0,0177**			0,1317***	-0,0151			0,0228	-0,0402			0,027	0,0171*	
		5,5814	-2,503			3,5036	-0,9364			0,3033	-1,1334			1,08	2,120	

"Notes: This table provides the estimation results for the full sample period and three sub-periods under down market conditions. The model specification is as follow: $\boldsymbol{CSAD_t^{DOWN}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}^{DOWN}|\boldsymbol{R_{m,t}^{DOWN}}| + \boldsymbol{\beta_2}^{DOWN}(\boldsymbol{R_{m,t}^{DOWN}})^2 + \boldsymbol{\varepsilon_t}$. Where $CSAD$ is the dependent variable. $|\boldsymbol{R_{m,t}^{DOWN}}|$ is the absolute value of average market returns in down markets. $(\boldsymbol{R_{m,t}^{DOWN}})^2$ is the corresponding quadratic term. This research sorts the sample into two groups based on the daily idiosyncratic volatility index. Group 1 includes stocks during the period of low idiosyncratic volatility and group 3 includes stocks during the period of high idiosyncratic volatility. **BOLD** values imply the occurrence of herding. This paper also tests the difference between group 1 and group 3 by using a t-test (G1-G3). The sample period is from 2003 to 2018. T-statistics is in parentheses and is corrected for heteroskedasticity and autocorrelation by (Newey & West, 1987). ***, **, and * denote significant level at the *1%*, *5%* and *10%* level, respectively."

Table 4 : Herding in Up Markets within Stock Portfolios of Idiosyncratic Volatility.

		Rising market															
		Full Sample Period				*BFC* Period				*FC* Period				*AFC* Period			
Market																	
		β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2	β_0	β_1	β_2	Adj-R^2
S.H.S.A	Group1	0.0243***	0.0350***	0.0320***	0.000	0.0212***	0.0243***	**-0.0062*** **	0.000	0.0135***	0.0005	0.0020	0.000	0.0200***	0.0198***	0.0017***	0.001
		40.039	13.467	12.314		12.390	5.511	-3.203		4.623	0.057	0.577		21.660	11.353	3.684	
	Group2	0.0320***	0.0721***	**-0.0154*** **	0.003	0.0370***	0.0182***	-0.0020	0.000	0.0055*	-0.0547***	0.0208***	0.001	0.0344***	0.0567***	**-0.0090*** **	0.002
		33.142	34.378	-19.247		20.070	3.716	-0.877		1.707	-5.206	3.623		30.280	25.457	-12.651	
	Group3	0.3471***	0.1453***	**-0.0408*** **	0.001	0.3837***	0.1486***	**-0.0461*** **	0.000	0.3337***	-0.0780	-0.0245	0.001	0.3595***	0.0825***	**-0.0083** **	0.001
		121.416	20.224	-12.519		45.561	8.123	-4.629		25.950	-1.337	-0.883		141.117	10.722	2.243	
	G3-G1		0,1103***	-0,0728***			0,1243***	-0,0399***			-0,0785	-0,0265			0,0627***	-0,01**	
			15,15	-24,26			6,741	-3,912			-1,340	-0,941			7,6034	-2,5	
S.H.S.B	Group1	0.0267***	0.0575***	**-0.0136*** **	0.005	0.0211***	0.0290**	-0.0052	0.001	-0.0019	-0.0920***	0.0661***	0.016	0.0370***	0.0517***	**-0.0111*** **	0.007
		7.683	10.894	-14.568		3.024	2.251	-1.461		-0.160	-2.695	5.257		8.401	8.481	-13.552	
	Group2	0.0420***	0.0631***	**-0.0080*** **	0.006	0.0385***	0.0448***	**-0.0092*** **	0.002	0.0184	0.0610	**-0.0344** **	0.002	0.0546***	0.0795***	**-0.0138*** **	0.006
		11.860	10.542	-6.398		5.442	3.739	-3.651		1.447	1.524	-2.015		12.065	9.153	-5.509	
	Group3	0.4006***	0.1888***	-0.0328	0.007	0.3738***	0.1325	-0.0067	0.009	0.3901***	0.0945	**-0.0831** **	0.003	0.4219***	0.2451***	**-0.0599*** **	0.007
		39.512	3.258	-1.145		16.968	1.063	-0.108		16.734	1.231	-2.079		40.277	10.321	-8.332	
	G3-G1		0,1313**	-0,0192			0,1035	-0,0015			0,1865**	-0,1492***			0,1934***	-0,0488***	
			2,2554	-0,66			0,823	-0,024			2,215	-3,547			7,817	-6,901	
S.Z.S.A	Group1	0.0391***	0.0929***	**-0.0260*** **	0.004	0.0239***	0.0336***	**-0.0118*** **	0.000	0.0405***	0.0448***	**-0.0282*** **	0.001	0.0362***	0.1159***	**-0.0314*** **	0.007
		47.215	52.330	-46.052		11.058	5.950	-4.588		12.065	4.677	-6.881		39.591	56.955	-44.516	
	Group2	0.0676***	0.1393***	**-0.0449*** **	0.006	0.0320***	0.0182***	-0.0021	0.000	-0.0051	-0.0092	**-0.0230*** **	0.003	0.0629***	0.1471***	**-0.0511*** **	0.008
		65.129	57.255	-44.489		13.367	2.859	-0.686		-1.230	-0.667	-2.824		8.972	57.108	-48.564	
	Group3	0.3683***	0.1214***	**-0.0329*** **	0.000	0.3584***	0.1135***	-0.0271	0.000	0.4386***	-0.2331	0.0810	0.000	0.3735***	0.0966***	**-0.0236*** **	0.000
		64.834	5.751	-2.909		37.002	3.809	-1.290		11.489	-1.506	0.683		63.784	5.174	-3.136	
	G3-G1		0,0285	-0,0069			0,0799**	-0,0153			-0,2779	0,1092			-0,0193	0,0078	
			1,3510	-0,624			2,611	-0,72			-1,78	0,917			-1,01	0,967	

S.Z.S.B	Group1	0.0155***	0.0378***	**-0.0087*** **	0.002	0.0271***	0.0359**	-0.0073	0.001	0.0239**	-0.0520*	0.0345***	0.005	0.0247***	0.0334***	**-0.0064*** **	0.002
		4.590	6.823	-7.263		4.038	2.450	-1.484		2.064	-1.855	3.157		5.753	5.480	-6.441	
	Group2	0.0459***	0.0620***	**-0.0082*** **	0.005	0.0493***	0.0476***	**-0.0081** **	0.002	0.0370***	0.1606***	**-0.0705*** **	0.010	0.0505***	0.0713***	**-0.0130*** **	0.004
		13.031	9.310	-4.565		7.260	3.627	-2.235		3.105	5.410	-6.470		11.122	8.612	-5.320	
	Group3	0.3344***	0.1348***	**-0.0177** **	0.006	0.3045***	0.1921***	**-0.0411*** **	0.010	0.3721***	0.0521	-0.0474	0.001	0.3600***	0.0977***	0.0007	0.005
		49.759	7.259	-2.199		27.349	6.642	-3.405		16.361	0.741	-1.415		37.656	3.211	0.048	
	G3-G1		0,097***	-0,009			0,1562***	-0,0338**			0,1041	-0,0819*			0,0643*	0,0071	
			4,868	-1,116			4,78	-2,6			1,3807	-2,354			2,101	0,472	

"**Notes:** This table provides the estimation results for the full sample period and three sub-periods under rising market conditions. The model specification is as follow: $\boldsymbol{CSAD_t^{UP} = \beta_0 + \beta_1{}^{UP}\left|R_{m,t}^{UP}\right| + \beta_2{}^{UP}\left(R_{m,t}^{UP}\right)^2 + \beta_3 CSAD_{t-1}^{UP} + \varepsilon_t}$ .Where $CSAD$ is the dependent variable. $\left|\boldsymbol{R_{m,t}^{UP}}\right|$ is the absolute value of average market returns in up markets. $\left(\boldsymbol{R_{m,t}^{UP}}\right)^2$ is the corresponding quadratic term. This research sorts the sample into two groups based on the daily idiosyncratic volatility index. Group 1 includes stocks during the period of low idiosyncratic volatility and group 3 includes stocks during the period of high idiosyncratic volatility. This paper also tests the difference between group 1 and group 3 by using (Paternoster *et al.*, 1998) test (G1-G3). **BOLD** values imply the occurrence of herding. The sample period is from 2003 to 2018. T-statistics is in parentheses and is corrected for heteroskedasticity and autocorrelation by (Newey & West, 1987). ***, **, and * denote significant level at the *1%*, *5%* and *10%* level, respectively."

Table 5 : Asymmetric Reaction Examination in Up and Down Markets within Stock Portfolios of Idiosyncratic Volatility.

			Full Sample Period	*BFC* Period	*FC* Period	*AFC* Period
Markets						
S.H.S.A	Group1	$\beta_1^{P} - \beta_1^{DOWN}$	0,016***	0,002	0,0437***	0,011***
			5,65685425	0,31234752	3,03004982	3,8890873
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0342***	-0,0023	0,0359***	0,0009
			34,2	-0,8131728	4,71390094	0,9
	Group2	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0301***	-0,0123*	-0,1069***	-0,0379***
			-10,641957	-1,9209373	-10,798531	-13,399674
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0057***	-0,0123***	0,0359***	0,0113***
			4,03050865	-5,5007272	6,34628336	7,99030663
	Group3	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0588***	0,0196	-0,1908***	-0,0822***
			-5,939697	0,83650762	-2,8592493	-7,2655222
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0042	-0,0358***	0,0548	0,0172***
			0,98994949	-3,0698247	1,69927586	3,44
S.H.S.B	Group1	$\beta_1^{UP} - \beta_1^{DOWN}$	0,0385***	-0,0179	-0,0598	0,0032
			4,92941988	-0,9369288	-1,1390993	0,37712362
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0342***	0,0069	0,0465**	-0,0001
			24,1830519	1,2197592	2,17280231	-0,0707107
	Group2	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0301***	-0,0344*	0,0739	0,0739***
			-3,2648034	-1,7907925	1,33943645	5,80613235
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0057**	-0,0069	-0,0535**	-0,0078*
			2,54911749	-1,38	-2,3597838	-2,1633308
	Group3	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0588	-0,2531*	-0,0263	0,0605
			-0,9423997	-1,9457146	-0,2430916	1,5747521
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0042	0,0978	-0,0178	-0,0359***
			0,98994949	1,53867952	-0,3266743	-3,1486383
S.Z.S.A	Group1	$\beta_1^{UP} - \beta_1^{DOWN}$	0,0602***	0,0204*	0,1378***	0,0897***
			21,2839141	2,21269067	7,30338539	31,7137391
		$\beta_2^{UP} - \beta_2^{DOWN}$	-0,0178***	-0,0124	-0,0915***	-0,0257***
			-12,586501	-2,922708	-9,2904174	-18,172644
	Group2	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0031	0,004	-0,1205***	0,0274***
			-1,0960155	0,51214752	-6,3072583	7,59939269
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0015	-0,0228	0,0338***	-0,0047***
			1,06066017	-6,3235822	3,38	-3,3234019
	Group3	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,0109	-0,094	-0,3626*	-0,0791***
			-0,4597887	-2,1789871	-1,9077606	-3,7624033
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0234*	0,0155	0,1865	0,018**
			1,99919692	0,58710436	1,44050881	2,10674065
S.Z.S.B	Group1	$\beta_1^{UP} - \beta_1^{DOWN}$	-0,002	-0,0016	-0,0994**	-0,0091
			-0,2357023	-0,0870285	-2,2661249	-0,804334
		$\beta_2^{UP} - \beta_2^{DOWN}$	0,0108***	0,007	0,0489***	0,0024
			7,63675324	0,74199852	4,96504275	1,69705627
	Group2	$\beta_1^{UP} - \beta_1^{DOWN}$	0,0125	0	0,1692***	0,0258**
			1,26269068	0	3,85742797	2,28041937
		$\beta_2^{UP} - \beta_2^{DOWN}$	-0,0001	0	-0,1017***	-0,0063**

		-0,0353553	0	-5,9720296	-2,2273864
Group3	$\boldsymbol{\beta_1}^{UP} - \boldsymbol{\beta_1}^{DOWN}$	-0,0109	0,0229	-0,0181	0,0282
		-0,4164676	0,52126291	-0,185468	0,73401668
	$\boldsymbol{\beta_2}^{UP} - \boldsymbol{\beta_2}^{DOWN}$	0,0108	-0,0117	0,0072	-0,0076
		1,01597854	-0,6345216	0,15427784	-0,4470588

"**Notes:** This table reports the estimation results of the test difference between up and down market under three groups of idiosyncratic volatility for the full sample, *BFC*, *FC*, and *AFC* periods. For this purpose, this study uses (Paternoster *et al.*, 1998) formula which is as follow: $Z = \frac{\beta_1 - \beta_2}{\sqrt{(SE\beta_1)^2 + (SE\beta_2)^2}}$. Where: $SE\beta$ is the standard error of β. ***, **, and * denote significant level at the *1%*, *5%*, and *10%* level, respectively."

5. Conclusion

When undiversified investors face the risk of information scarcity, the idiosyncratic volatility of their stocks increases and may become essential for herding. Therefore, they tend to imitate the investment strategies of other investors rather than executing trades according to their own beliefs and personal information. Thus, the purpose of this study in investigating the influence of idiosyncratic volatility on market participants' herding activity in the Chinese Stock Market from 2003 to 2018. For this reason, this study employs the cross-sectional absolute deviation (CSAD) as a metric dispersion of returns to detect herding propensity.

The empirical findings show that during severe price fluctuations, the estimates of β_1 and β_2 for CSAD in both criterion levels are statistically positive in the entire sample period for whole markets, suggesting that stock return dispersion appears to increase during times of extreme price movement, contradicting the presence of herding activity in the Chinese Stock Market. However, when the entire sample is divided into sub-periods, only the FC periods display signs of herding, suggesting that investors can behave irrationally and change their investment strategy significantly during times of turmoil.

In addition, using (Chang et al., 2000)'s model, the findings indicate empirical evidence of herding tendency in the Chinese stock market from 2003 to 2018, as well as overall sub-periods: BFC, FC and AFC. This conclusion backs up the findings of recent research on the occurrence of herding activity in emerging markets (Dang & Lin, 2016); (Vo & Phan, 2017).

The analysis also looks at whether herding activity varies based on the degree of idiosyncratic volatility in different sub-periods. The sample is divided into three main classes, each with a different level of idiosyncratic volatility. Stocks in Group 1 have the lowest idiosyncratic volatility, while stocks in Group 3 have the highest idiosyncratic volatility, and stocks in Group 2 have the highest idiosyncratic volatility. The bulk of β_2 coefficients are strongly negative, according to the empirical findings. This result reveals the existence of a non-linear model over time and through groups.

Furthermore, the significant difference between groups 3 and 1 provides additional evidence of herding in larger idiosyncratic volatility stock portfolios. For instance, in the full sample period, the test difference shows that larger idiosyncratic volatility stock portfolios encourage herding in the whole markets. However, only a small evidence in Shenzhen B (S.Z.S.B) during the BFC period. During the FC period, the test difference between groups 3 and 1 provides also a supplementary indication of herding behavior in larger idiosyncratic volatility stock portfolios, especially in Shanghai A (S.H.S.A), Shanghai B (S.H.S.B), and weak evidence in Shenzhen B

(S.Z.S.B), implying that initiative-based trade behavior is usually apparent during FC periods. During the AFC period, only Shanghai A (S.H.S.A), Shanghai B (S.H.S.B) where investors significantly tend to herd with larger idiosyncratic volatility stock portfolios, while with a small magnitude in Shenzhen A (S.Z.S.A).

In addition, the analysis looks at the asymmetric impact of herding in up and down markets with varying levels of idiosyncratic volatility over three sub-periods and the entire sample period. During falling markets, herding in whole markets is more pronounced in the highest idiosyncratic volatility stock portfolios, as demonstrated by the large gap between the two classes over the entire sample span. During the BFC period, herding is only observable with a greater magnitude in the largest idiosyncratic volatility stock portfolios in both Shanghai B (S.H.S.B) and Shenzhen A (S.Z.S.A). During the FC period, herding is more noticeable in the largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A) and Shenzhen A (S.Z.S.A) and with weak evidence in Shanghai B (S.H.S.B). During the AFC period, herding is more apparent in largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A) and Shenzhen A (S.Z.S.A) and in smallest idiosyncratic volatility stock portfolios in Shanghai B (S.H.S.B). During the rising market, herding is only pronounced with a greater magnitude in the largest idiosyncratic volatility stock portfolios in Shanghai A (S.H.S.A). During the BFC period, herding is again evidenced in Shanghai A (S.H.S.A) and with a little evidence in Shenzhen B (S.Z.S.B). During the FC period, herding in evidenced only in Shanghai B (S.H.S.B) and with weak evidence in Shenzhen B (S.Z.S.B). During the AFC period, herding is significantly observed in Shanghai B (S.H.S.B) and with weak evidence in Shanghai A (S.H.S.A). In conclusion, this research shows that herding occurs in the Chinese stock market, that it differs with levels of idiosyncratic volatility, and that investment behavior tends to vary during the three sub-periods.

The majority of studies look at idiosyncratic volatility through the prism of investor rationality, ignoring the behavioral element of it, and only a few studies show a clear correlation between idiosyncratic volatility and herding conduct. As a consequence, a deeper understanding of the relationship between idiosyncratic volatility and herd behavior is essential. As a result, this study contributes to existing literature by exploring the effects of idiosyncratic volatility on herding behavior in greater detail, by looking into the nature of herding and its asymmetric influence under extreme market conditions and market dynamics, conducting a sub-period analysis focused on the Great Financial Crisis. Overall, the results of this study indicate that idiosyncratic volatility is an essential component and determinant of herding conduct in the Chinese Stock Market. The findings indicate that herding occurs in the Chinese stock market, that it differs with idiosyncratic volatility, and that investment behavior tends to be different during three sub-periods.

Academic researchers, investors, and policymakers will benefit from this paper's results in both academia and practice. To begin, this study adds to the current literature by presenting empirical evidence in the sense of an emerging market. Second, investors should be acknowledged to identify firms with high and low levels of idiosyncratic volatility and make plausible investment decisions, even in the case of companies with the low idiosyncratic volatility. They should also be able to understand the relationship between herding and idiosyncratic volatility, which may help them in taking better investment decisions and offsetting strategies. This will assist stock prices in getting closer to their fundamental values, thus improving market efficiency. Finally, this study suggests that policymakers focus more on enhancing information accuracy in order to achieve and maintain financial stability.

Future research can focus on herding behavior of institutional investors, as this study tested only firm level herding. This study has used only daily stock returns data, future researchers can test herding behavior using high frequency, weekly and monthly returns. This study has also used only market level data, future research can examine industry level data , (Bikhchandani & Sharma, 2001) state that herd might arise at the level of investments in a group of stocks, such as stocks of firms in an industry or in a country where investors might face similar information. Another reason is the degree of familiarity of sophisticated investors with certain industries, that allow un sophisticated investors to mimic their trading and investment strategies within these specific industries, thus, the occurrence of the herd. Therefore, studying industry herding might provide a high practical value. A further research might also explore some other financial anomalies such as lottery-type stocks, momentum effect, idiosyncratic risk puzzle as well as some Chinese specific elements that might influence herding such as the impact of financial market liberalization such as the effect of Stock-Connect Schemes “The Shanghai–Hong Kong Stock Connect (SH–HK–SC) and Shenzhen–Hong Kong Stock Connect (SZ–HK–SC) programs”, political tensions, recent pandemic effect, new financial regulations, information asymmetry effect, policy uncertainty effect and international shocks.

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