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Monetary policy, exchange rate fluctuation, and herding behavior in the stock market

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ABSTRACT

Interest rate and exchange rate are two important macroeconomic variables that exert considerable effects on the stock market. In this study, we investigate whether variations in interest and exchange rates induce herding behavior in the Chinese stock market. Empirical results indicate that interest rate increase and Chinese currency (CNY) depreciation will induce herding and this phenomenon is mainly manifested in down markets. Moreover, the herding level of the highest idiosyncratic volatility quintile portfolio is twice that of the lowest quintile portfolio which we consider evidence of intentional herding. This result is consistent with those of previous studies, which report that retail investors prefer and overweigh lottery-type stocks. Finally, we investigate the effects of monetary policy announcements and extreme exchange rate volatility on herding because these events elicit considerable public attention and may trigger collective behavior in the aggregate market.

1. Introduction

Interest rate and foreign exchange rate are two important macroeconomic variables in open economics that significantly affect the stock market. Interest rate represents the stance of the central bank on monetary policy; it affects stock prices through discount rate channels, expected future dividends, and equity premium (Bernanke & Kuttner, 2005). In particular, the worldwide low interest rate environment plays a significant role in improving the global stock market after the subprime crisis. Meanwhile, movements in exchange rates affect stock prices because of their influences on the cash flow and international competitiveness of firms, as well as on capital flows in and out of a country. Numerous studies have investigated the effects of interest rate variation or monetary policy shocks on stock returns (Thorbecke, 1997; Bjørnland & Leitemo, 2009). Other studies have explored the relationship between exchange rate and stock returns (Hau & Rey, 2006; Cho, Choi, Kim & Kim, 2016). However, to the best of our knowledge, few studies have considered the effects of variations in interest and exchange rates on investor behavior at the micro-level. In this study, we address this gap and examine the effects of variations in interest and exchange rates on herding behavior in the stock market. Herding in financial markets refers to a behavioral pattern in which investors suppress their own beliefs and base their investment decisions solely on the collective actions of the market (Christie & Huang, 1995). Existing empirical studies have documented herding behavior in different countries, particularly in emerging markets due to considerable information asymmetry and the lack of maturity in these markets (Chang, Cheng & Khorana, 2000; Chiang & Zheng, 2010). As an important emerging market that is primarily dominated by unsophisticated retail investors, the Chinese stock market provides an interesting setting to analyze herding behavior. Moreover, the recent uncertainty in the economic development of China has resulted in increased fluctuations in interest and exchange rates, as well as in the intensive response of the stock market to these variations. In this context, this study aims to answer the following questions: (1) Do interest and exchange rates induce herding behavior in the Chinese stock market? (2) Under what market conditions will investors respond intensively to variations in interest and exchange rates, and what types of stocks are most affected? (3) Do monetary policy announcements and extreme exchange rate volatility induce herding?

This study distinguishes itself from previous research and contributes to literature in the following aspects. First, this study is the first to examine the effects of variations in interest and exchange rates on herding behavior in the stock market. Our results indicate that interest rate increase and Chinese currency (hereafter CNY) depreciation will induce herding. This phenomenon is mainly manifested in down markets, thereby suggesting that investors respond intensively to bad news. Bikhchandani and Sharma (2000) distinguish between "spurious herding" (fundamental herding), in which investors facing similar decision problems and information sets make similar decisions, and "intentional herding" (non-fundamental herding), which indicates an obvious intent of investors to follow the behavior of others. These researchers suggest that spurious herding may increase the efficiency of financial markets, whereas intentional herding is expected to result in excess volatility and even financial instability. In this study, interest and exchange

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rates are public information that appears to lead to spurious herding. Nonetheless, the response to these fundamental changes by investors may unnecessarily improve the efficiency of the market, particularly under extreme interest rate or exchange rate volatility, because investors may overreact to unexpected information changes (Bondt & Thaler, 1985). Thus, this study investigates whether variations in interest and exchange rates can induce herding rather than overemphasize the pricing efficiency of fundamental herding.

Second, we propose a method to detect the occurrence of intentional herding in the aggregate market. Macro information, such as interest rate and exchange rate, may induce spurious herding in the stock market; hence, questioning whether intentional herding occurs in this market is natural. With respect to this question, Holmes, Kallinterakis, and Ferreira (2013) analyze herding under different market conditions in Portugal and find that institutional herding is intentional driven by reputational reasons and/or informational cascades. Galariotis, Rong and Spyrou (2015) use the Fama-French three factors and the momentum factor to reflect common risk factors in stock valuation and decompose cross-sectional absolute deviation into fundamental and non-fundamental information parts. Unlike in previous studies, we determine the occurrence of intentional herding by examining whether investors herd on the idiosyncratic risk of stocks. Idiosyncratic volatility (IVOL) measures the idiosyncratic risk of a firm that does not arise from the systematic risk factors. Therefore, the occurrence of significantly varied herding coefficients among different IVOL portfolios comes from idiosyncratic risks rather than from fundamental changes that affect the entire market. Consequently, this phenomenon can be attributed to intentional herding. Consistent with our predictions, we find that the herding level of the highest IVOL quintile portfolio is twice that of the lowest quintile portfolio, which proves the occurrence of intentional herding in the Chinese stock market. After controlling for institutional ownership or number of institutions, the herding levels of the two highest IVOL quintiles weaken, thereby indicating that retail investors play an important role in reinforcing herding with the highest IVOL stocks.

Third, we emphasize the effects of monetary policy announcements and extreme exchange rate volatility on herding behavior given that such events elicit considerable public attention and are likely to affect public behavior. The empirical results indicate that a contractionary monetary policy shock (raising the benchmark deposit rate) induces herding, whereas an easy monetary policy shock (cutting the benchmark deposit rate or cutting the deposit reserve ratio) induces the aggregate market to undergo "anti-herding". Furthermore, a 1% CNY depreciation level during extreme exchange rate volatility will induce herding, whereas a 1% CNY appreciation level will not.

The remainder of the paper is organized as follows. Section 2 reviews the literature on the effects of monetary policy and exchange rate on stock returns and herding behavior in financial markets. Section 3 introduces the methodology and data used in this study. Section 4 presents the empirical results, and Section 5 concludes the study.

2. Literature review

This section provides a short review of the effects of monetary policy and exchange rate on stock returns and herding behavior in financial markets, supporting the hypothesis in this study that variations in interest and exchange rates may induce herding in the stock market.

2.1. Monetary policy, exchange rate, and stock returns

Thorbecke (1997) investigates how stock returns respond to monetary policy shocks measured by innovations in the federal funds rate and non-borrowed reserves. The results indicate that expansionary monetary policy prompts stock prices in short time horizons and exerts considerable effects on small firms. Bernanke and Kuttner (2005) adopt "event study" to investigate the impact of change in monetary policy on equity prices; they find that an unanticipated 25-basis-point cut in the federal funds rate target leads to a 1% increase in stock indexes. Bjørnland and Leitemo (2009) propose a structural vector autoregression model that combines short-run and long-run restrictions to solve the simultaneity problem in identifying monetary policy and stock price shock; they determine that stock prices fall immediately by 7% to 9% due to an unanticipated 100-basis-point increase. In general, monetary policy plays an important role in stock price movements. An unanticipated interest rate increase leads to a decline in stock prices given its influence on discount rate channels, expected future dividends and equity premium.

By contrast, the relationship between exchange rate and stock returns varies. Dornbusch and Fischer (1980) focus on the current account and assert that stock prices are beneficial to deprecation of local currency because of the increased international competitiveness of local firms and their profits. Hau and Rey (2006) develop a theoretical model in which investors face incomplete hedging of foreign exchange rate risk and are required to rebalance the foreign equity portfolio following a gain. Such an approach leads to the depreciation of relevant foreign currency, and a negative relationship between stock returns and currency return appears. Cho et al. (2016) argue that the correlation between currency and stock returns differs between emerging markets and developed markets due to capital flows in and out of these markets along with global stock market conditions. When the global stock market is down, capital tends to move out of emerging markets and into developed countries, thereby generating a positive correlation between currency and stock returns in emerging markets and a negative correlation in developed markets. The same correlations remain in global up markets. Lin (2012) examines the co-movement between exchange rate and stock returns across different industries in emerging Asian markets. The findings show that co-movement is not stronger within export-oriented industries, implying that the relationship between exchange rates and stock returns is mainly driven by capital account, which supports the view of capital flows. Emerging markets generally benefit from local currency appreciation due to capital flows into these markets, whereas local currency depreciation is regarded as "bad" news in these stock markets.

2.2. Herding behavior in financial markets

Empirical studies have focused on the herding behavior of institutional investors and financial analysts in financial markets (Sias, 2004; Choi & Sias, 2009; Huang, Wu & Lin, 2016; Bernhardt, Campello & Kutsoati, 2006). By contrast, the focus of the current study is to investigate herding in the aggregate market. Christie and Huang (1995) first use the cross-sectional standard deviation of stock returns to capture herding towards market consensus. They find a relatively high return dispersion at times of large price movements, which is considered evidence against herding behavior. Chang et al. (2000) use the cross-sectional absolute deviation to measure return dispersion and apply a non-linear model to detect herding behavior in their study. Their empirical results show that significant evidence of herding is recorded in South Korea and Taiwan, partial evidence is observed in Japan, and no evidence is found in the US and Hong Kong. Hwang and Salmon (2004) propose an alternative method to measure herding based on the cross-sectional dispersion of asset sensitivity to various fundamental factors. They find significant movements and persistence of herding in the US and South Korea. Chiang and Zheng (2010) modify the method proposed by Chang et al. (2000) and examine herding behavior in global stock markets. Their empirical results provide evidence of herding in advanced stock markets and Asian markets, except for the US. Huang, Lin, and Yang (2015) examine herding patterns under various IVOL portfolios in Taiwan stock market, which inspires us to detect intentional herding by comparing herding coefficients in different IVOL portfolios.

With regard to herding studies in the Chinese stock market, Demirer and Kutan (2006) use the method proposed by Christie and Huang

(1995) and find no herding in the Chinese stock market. Tan, Chiang, Mason, and Nelling (2008) examine herding behavior in dual-listed Chinese A-share and B-share stocks and report significant evidence of herding in both markets under rising and falling market conditions. Yao, Ma, and He (2014) examine the occurrence of herding behavior in Chinese A-share and B-share stock markets; they find no herding in the A-share market but strong herding in the B-share market. Further empirical results indicate that herding is more prevalent at the industry-level and is stronger for the largest, smallest, and growth stocks. Hilliard and Zhang (2015) report significant herding behavior in the Chinese stock market between 2002 and 2012, suggesting that herding level has decreased after 2006 because information asymmetry issues have been alleviated.

3. Methodology and data description

3.1. Methodology

Christie and Huang (1995) first propose a method for detecting herding behavior using cross-sectional stock returns. They argue that dispersion in stock returns during normal periods will increase with the absolute value of market returns as predicted by rational asset pricing models. However, investors are likely to suppress their beliefs in the market consensus during extreme market movements and herding will be prevalent. Thus, Christie and Huang (1995) propose the cross-sectional standard deviation method to measure stock return dispersion:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-R_{m,t}\right)^2}{(N-1)}} \tag{1}$$

where $R_{i,t}$ is the return of individual stock i on day t. $R_{m,t}$ is the cross-sectional average of N stock returns in the portfolio on day t.

$CSSD_t$, which is defined as the squared return-deviation, tends to be sensitive to the outlier. Chang et al. (2000) propose the cross-sectional absolute deviation $CSAD_t$ to measure stock return dispersion as shown in Eq. (2):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t}-R_{m,t}\right| \tag{2}$$

Chang et al. (2000) state that rational asset pricing models imply a linear relationship between $CSAD_t$ and return on the market portfolio. However, if market participants tend to follow the aggregate market behavior and herd under the market stress conditions, then the linear relationship between $CSAD_t$ and return on the market portfolio will not hold. Consequently, a non-linear regression model adopted by Chang et al. (2000) is given as:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3}$$

Chang et al. (2000) argue that the coefficient on the non-linear term will be significantly negative in the case of herding.

The pivotal issue in this study is to test whether variations in interest and exchange rates induce herding behavior in the stock market. Thus, we adopt the herding testing method proposed in Chang et al. (2000) and augment Eq. (3) as follows:

$$\begin{aligned} CSAD_t = {} & \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \gamma_3 \Delta int_t Dum_{t,1} R_{m,t}^2 \\ & + \gamma_4 \Delta int_t \left(1-Dum_{t,1}\right) R_{m,t}^2 + \gamma_5 \Delta ex_t Dum_{t,2} R_{m,t}^2 \\ & + \gamma_6 \Delta ex_t \left(1-Dum_{t,2}\right) R_{m,t}^2 + \varepsilon_t \end{aligned} \tag{4}$$

where Δint_t and Δex_t represent the changes in interest and exchange rates on day t, respectively. We adopt the interbank seven-day offered rate to measure interest rate. The interbank market exhibits the highest degree of interest rate marketization in China, and the Chinese central bank sends policy signals and affects interbank interest rate through open market operations in this market. Therefore, interbank seven-day offered rate plays a role similar to the policy rate in China. Exchange rate is measured by USD to CNY. Thus, $\Delta ex_t < 0$ indicates CNY appreciation, and vice versa. $Dum_{t,1}$ is the dummy variable that takes one when interest rate is increasing ($\Delta int_t > 0$) and zero otherwise. $Dum_{t,2}$ is one when local currency appreciates ($\Delta ex_t < 0$) on day t and zero otherwise. From Eq. (4), the partial effect of $\Delta R_{m,t}^2$ on $\Delta CSAD_t$ is:

$$\begin{aligned} \frac{\partial CSAD_t}{\partial R_{m,t}^2} = {} & \gamma_2 + \gamma_3 \Delta int_t Dum_{t,1} + \gamma_4 \Delta int_t \left(1-Dum_{t,1}\right) \\ & + \gamma_5 \Delta ex_t Dum_{t,2} + \gamma_6 \Delta ex_t \left(1-Dum_{t,2}\right) \end{aligned} \tag{5}$$

As stated earlier, China is an emerging market. Thus, interest rate increase and CNY depreciation will generally reduce the attractiveness of stocks, whereas stock valuation will benefit from interest rate decrease and CNY appreciation. Hence, if interest rate increase and CNY depreciation are regarded as bad news in the stock market and induce herding behavior, then γ_3 and γ_6 are significantly negative because $\Delta int_t Dum_{t,1}$ and $\Delta ex_t(1-Dum_{t,2})$ are non-negative terms; as the degree of interest rate increase or CNY depreciation becomes large, the herding level will be strong. Similarly, if interest rate decrease and CNY appreciation are regarded as good news and induce herding, then γ_4 and γ_5 will be significantly positive because $\Delta int_t(1-Dum_{t,1})$ and $\Delta ex_t Dum_{t,2}$ are non-positive terms. Consequently, γ_3 to γ_6 are used to test the effects of variations in interest and exchange rates on herding behavior.

Subsequently, we investigate whether herding is asymmetric in up and down markets, as well as the effects of variations in interest and exchange rates on herding behavior under different market conditions. Then, we run the following empirical models.

If $R_{m,t}>0$, then

$$\begin{aligned} CSAD_t^{UP} = {} & \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}\left(R_{m,t}^{UP}\right)^2 + \gamma_3^{UP}\Delta int_t Dum_{t,1}\left(R_{m,t}^{UP}\right)^2 \\ & + \gamma_4^{UP}\Delta int_t\left(1-Dum_{t,1}\right)\left(R_{m,t}^{UP}\right)^2 + \gamma_5^{UP}\Delta ex_t Dum_{t,2}\left(R_{m,t}^{UP}\right)^2 \\ & + \gamma_6^{UP}\Delta ex_t\left(1-Dum_{t,2}\right)\left(R_{m,t}^{UP}\right)^2 + \varepsilon_t \end{aligned} \tag{6}$$

If $R_{m,t}<0$, then

$$\begin{aligned} CSAD_t^{DOWN} = {} & \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}\left(R_{m,t}^{DOWN}\right)^2 \\ & + \gamma_3^{DOWN}\Delta int_t Dum_{t,1}\left(R_{m,t}^{DOWN}\right)^2 \\ & + \gamma_4^{DOWN}\Delta int_t\left(1-Dum_{t,1}\right)\left(R_{m,t}^{DOWN}\right)^2 \\ & + \gamma_5^{DOWN}\Delta ex_t Dum_{t,2}\left(R_{m,t}^{DOWN}\right)^2 \\ & + \gamma_6^{DOWN}\Delta ex_t\left(1-Dum_{t,2}\right)\left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t \end{aligned} \tag{7}$$

In Eqs. (6) and (7), $R_{m,t}^{UP}$ ($R_{m,t}^{DOWN}$) is the equal-weighted portfolio returns at time t when the market rises (falls). $CSAD_t^{UP}$ ($CSAD_t^{DOWN}$) is the $CSAD_t$ that corresponds to $R_{m,t}^{UP}$ ($R_{m,t}^{DOWN}$). From our point of view, good news may amplify herding behavior in up markets, whereas bad news will amplify herding in down markets. If this scenario is true, then γ_4^{UP} and γ_5^{UP} are significantly positive in up markets, whereas γ_3^{DOWN} and γ_6^{DOWN} are significantly negative in down markets. By contrast, good news in down days or bad news in up days will intensify the divergence of opinions of investors in the stock market. Consequently, good news may weaken herding in down markets and bad news may weaken herding in up markets. That is, γ_4^{DOWN} and γ_5^{DOWN} will be significantly negative, whereas γ_3^{UP} and γ_6^{UP} will be significantly positive.

Furthermore, we identify intentional herding by examining whether investors herd on idiosyncratic risk. We measure idiosyncratic risk following Ang, Hodrick, Xing, and Zhang (2006), as follows:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + h_i SMB_t + s_i HML_t + \varepsilon_{it} \tag{8}$$

where $r_{i,t}$ is the excess return for stock i on day t. MKT_t, SMB_t, and HML_t are the daily excess returns on the market portfolio, size factor, and value factor, respectively, as defined by Fama and French (1993, 1996). α_i measures the mispricing of asset i. In each month, the daily excess return of individual stock is regressed on the daily Fama-French three factors, and IVOL is defined as $\sqrt{var(\varepsilon_{it})}$. We require a minimum of 15 trading days for each stock in a month to reduce the impact of infrequent trading on IVOL estimation. After calculating the IVOL of each stock every month, we can obtain $CSAD_t$ in quintile portfolios sorted by IVOL of each individual stock. We then run Eqs. (3) and (4) to compare herding coefficients among different IVOL quintile portfolios.

Finally, we examine the effects of monetary policy announcements and extreme exchange rate volatility on herding behavior. The benchmark deposit rate and deposit reserve ratio are the two main monetary policy tools in China. The former is the indicative rate of commercial banks provided by the Chinese central bank. Since 2005, the Chinese central bank has announced raising the benchmark deposit rate 12 times, raising the deposit reserve ratio 28 times, cutting the benchmark deposit rate 13 times, and cutting the deposit reserve ratio 12 times. To investigate the effects of these events, we augment Eq. (3) as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \omega_j Dum_j R_{m,t}^2 + \varepsilon_t \ (j = 1, 2, 3, 4, 5, 6) \tag{9}$$

Various dummy variables are included in Eq. (9). A dummy is included one at a time from Dum_1 to Dum_6, where Dum_1 to Dum_4 denote dummy variables that take the value of one a day after the central bank raises the benchmark deposit rate, raises the deposit reserve ratio, cuts the benchmark deposit rate, cuts the deposit reserve ratio respectively and zero otherwise. Dum_5 takes the value of one on the day when Δex_t lies in the extreme 1% lower tail of the entire Δex_t distribution (appreciation), whereas Dum_6 is one when Δex_t lies in the extreme 1% upper tail of the entire Δex_t distribution (depreciation).

3.2. Data

All necessary data related to Chinese listed stocks for empirical analysis, including stock prices, market capitalization, book-to-market (BTM) values, volume, institutional ownership, number of institutions, and macroeconomic variables (e.g., inter-bank seven-day offered rate and USD to CNY exchange rate), are obtained from the Wind database. The daily Fama-French three factors are downloaded from the RESSET database. To calculate stock returns, the daily stock prices for all the listed firms on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from July 21, 2005 to June 30, 2016 are collected, and daily stock returns are calculated as $R_t = 100 \times (\log(P_t) - \log(P_{t-1}))$. The starting time of our sample is based on the fact that China experienced the exchange rate reform in July 2005 when the central bank adopted the managed floating exchange rate regime that references to a basket of currencies instead of pegging the US dollar only. The sample is readjusted by daily frequency because most of the firms will be filtered out if we choose only those that have been listed during the entire period. A total of 1358 firms are listed in July 2005, but the final sample contains 2832 firms. The final dataset includes 2660 daily observations, among which 1560 observations are classified into up markets, whereas 1100 observations are considered down markets.

Panel A of Table 1 provides the mean, median, standard deviation, maximum and minimum values of cross-sectional average return (R), and cross-sectional absolute deviation $CSAD$ for the full sample, smallest and largest market capitalization stocks, lowest and highest BTM stocks, and lowest and highest IVOL stocks. In general, large stocks, growth stocks and high IVOL stocks have high mean values of R. Growth stocks and high IVOL stocks have high mean values of $CSAD$, suggesting that these stocks exhibit high variations. Panel B indicates that the maximum and minimum values of Δint_t in our sample period are 4.0610% and −6.7145%, respectively. This result suggests that interest rate may exhibit strong volatility on a daily basis. Meanwhile, the maximum and minimum of Δex_t are 0.1136 and −0.1665, respectively.

Table 1
Summary statistics.

Sample	Variables	Mean	Median	SD	Max	Min
Panel A: summary statistics of cross-sectional average return (R) and cross-sectional absolute deviation ($CSAD$)						
All stocks	R	0.0927	0.3463	2.2975	9.2990	−10.2633
	$CSAD$	1.7819	1.6463	0.5616	5.5823	0.4523
Small stocks	R	0.0433	0.3750	2.375	9.3097	−10.2080
	$CSAD$	1.7152	1.5814	0.571	5.1451	0.4837
Large stocks	R	0.1117	0.2384	2.1179	9.4909	−10.1908
	$CSAD$	1.8024	1.6656	0.6352	7.1528	0.3793
Growth stocks	R	0.2119	0.4400	2.2230	9.3341	−9.8407
	$CSAD$	2.1372	2.0085	0.6675	6.3724	0.4255
Value stocks	R	−0.0050	0.2386	2.3171	9.3895	−10.4043
	$CSAD$	1.4495	1.3250	0.5303	5.9748	0.3661
Low IVOL stocks	R	−0.1097	0.1463	2.2616	9.2800	−10.3741
	$CSAD$	1.1089	1.0030	0.4546	5.1262	0.3961
High IVOL stocks	R	0.4058	0.7286	2.3571	9.5053	−9.8454
	$CSAD$	2.6763	2.5247	0.7846	8.4114	0.2622
Panel B: summary statistics of interest and exchange rates						
Interest rate		2.9421	2.7536	1.2521	12.2521	0.9159
Δint_t		0.0003	0.0003	0.4112	4.0610	−6.7145
Exchange rate		6.7913	6.6245	0.6325	8.1128	6.0930
Δex_t		−0.0006	−0.0002	0.0078	0.1136	−0.1665

Note: This table reports the mean, median, standard deviation, maximum and minimum values of cross-sectional average return (R), and cross-sectional absolute deviation ($CSAD$) for the whole sample and different portfolios. Relevant information on interest and exchange rates is also reported. Interest and exchange rates are measured via the interbank seven-day offered rate and USD to CNY exchange rate, respectively.

4. Empirical results

4.1. Herding behavior and the effects of variations in interest and exchange rates

Table 2 provides the empirical results based on Eqs. (3) and (4) for the full sample, up markets, and down markets. Panel A estimates Eq. (3) and shows that herding coefficients γ_2 are all significantly negative for the full sample, up markets and down markets. In addition, herding is evidently stronger in down markets than in up markets (−0.0257 compared with −0.0159), which is consistent with previous studies (Chang et al., 2000; Yao et al., 2014). These results indicate that the linear relationship between $CSAD_t$ and return on market portfolio does not hold, and that investors tend to cluster around the aggregate market return under market stress. Fig. 1 illustrates the non-linear relationship between $CSAD_t$ and market returns. The quadratic relation in Eq. (3) suggests that $CSAD_t$ reaches its maximum value when $R^*_{m,t} = -(\gamma_1/2\gamma_2)$, indicating that the certain thresholds are $R^{UP*}_{m,t} = 3.74\%$ and $R^{DOWN*}_{m,t} = -6.42\%$ in up and down markets, respectively. That is, as $R_{m,t}$ increases in up markets, $CSAD_t$ increases at a decreasing rate when $R_{m,t} < R^{UP*}_{m,t}$, whereas $CSAD_t$ decreases monotonically when $R_{m,t} > R^{UP*}_{m,t}$. A similar case is found in down markets.

Panel B provides the regression results based on Eq. (4) when considering the effects of variations in interest and exchange rates on herding. For the full sample, the estimated results show that γ_3 and γ_6 are significantly negative, whereas γ_4 and γ_5 are insignificant. These findings suggest that interest rate increase or CNY depreciation will induce herding, whereas interest rate decrease or CNY appreciation will not. This result indicates that investors respond more intensively to bad news than to good news. The empirical results in down markets are similar to the full sample estimations. However, we do not observe this phenomenon in up markets since γ_3, γ_4, γ_5, and γ_6 are all insignificant. These results indicate that the effects of interest rate increase and CNY depreciation on herding are mainly manifested in down markets.

Table 2
Testing for herding toward market consensus.

Sample	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	$\overline{R}^2$
Panel A: regressions results based on Eq. (3)								
Full sample	1.5367***	0.1856***	−0.0111***					0.11
	(50.6818)	(6.4041)	(−2.6681)					
Up market	1.5305***	0.1188***	−0.0159***					0.02
	(44.3309)	(3.4649)	(−3.1367)					
Down market	1.5505***	0.3299***	−0.0257***					0.27
	(38.9703)	(9.0559)	(−5.2744)					
Panel B: regressions results based on Eq. (4)								
Full sample	1.5404***	0.1800***	−0.0091**	−0.0052*	0.0004	−0.1743	−0.3368***	0.11
	(50.7544)	(6.2269)	(−2.1928)	(−1.8716)	(0.0926)	(−0.6732)	(−2.6452)	
Up market	1.5329***	0.1161***	−0.0148***	−0.0087	0.0089	−0.1120	0.2802	0.02
	(63.1697)	(5.2743)	(−3.7930)	(−1.6172)	(1.0335)	(−0.4245)	(0.7386)	
Down market	1.5576***	0.3196***	−0.0234***	−0.0063***	0.0011	−0.4606	−0.3662***	0.28
	(39.4273)	(9.0298)	(−4.6570)	(−3.2575)	(0.5297)	(−1.6377)	(−3.4787)	

Note: Panels A and B of this table report the regression results of Eqs. (3) and (4), respectively, for the full sample, up markets, and down markets. The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. $\overline{R}^2$ is the adjusted R^2.
*** Represents statistical significance at the 1% level.
** Represents statistical significance at the 5% level.
* Represents statistical significance at the 10% level.

4.2. Herding at size and BTM levels

Tables 3 and 4 report the regression results based on Eqs. (3) and (4) across different portfolios sorted by size and BTM value for the full sample and under different market conditions. Size-based quintile portfolios and BTM value-ranked portfolios are constructed based on month-end market capitalization and BTM values and are re-sorted every month to track the changes of each stock during the sample period.

Panel A of Table 3 shows that herding is observed across different sizes of quintile portfolios for the full sample, up markets and down markets. The herding level increases monotonically from the smallest to the largest portfolio in up markets. No obvious different herding patterns exist across these portfolios in down markets, but the largest portfolio displays the weakest herding. Small stocks are confronted with serious information asymmetry, which may cause them to easily follow the market consensus. Hence, determining that the herding level of the smallest portfolio is weakest for the full sample and in up markets is interesting. We propose two possible reasons to answer this question. First, many newly issued stocks are found in the smallest portfolio. These stocks may be less affected by market movement, such that a weak herding level in the smallest portfolio is observed. Second, large stocks are subject to great coverage by analysts and are likely to undergo fundamental herding. Yao et al. (2014) find that the largest quintile portfolio displays high herding level in the Chinese stock market. Panel B shows the effects of variations in interest and exchange rates on herding. For the full sample, as well as in down markets, CNY depreciation obviously induces herding at quintile portfolios with different sizes, whereas interest rate increase does not affect herding in the two

Fig. 1. Relationship between daily $CSAD_t$ and the corresponding equally weighted market return.

Table 3
Regression results of the daily $CSAD_t$ for portfolios sorted by market capitalization.

Sample	α	γ_1	γ_2	$\overline{R}^2$	Sample	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	$\overline{R}^2$
Panel A: regressions results based on Eq. (3)					Panel B: regressions results based on Eq. (4)								
Full sample					Full sample								
1 (Smallest)	1.5032***	0.1546***	−0.0078*	0.09	1 (Smallest)	1.5059***	0.1506***	−0.0059	−0.0035	0.0014	−0.0411	−0.3425***	0.09
	(48.9267)	(5.2631)	(−1.8347)			(48.7612)	(5.0890)	(−1.3667)	(−1.2573)	(0.3158)	(−0.1679)	(−2.6621)	
2	1.5516***	0.1642***	−0.0096**	0.09	2	1.5543***	0.1601***	−0.0080*	−0.0027	−0.0019	−0.0274	−0.3405***	0.09
	(51.7068)	(5.7001)	(−2.2866)			(51.4992)	(5.5198)	(−1.8933)	(−0.9769)	(−0.3931)	(−0.1144)	(−2.8592)	
3	1.5733***	0.1791***	−0.0115***	0.09	3	1.5768***	0.1739***	−0.0096**	−0.0056**	−0.0003	−0.1129	−0.3227**	0.09
	(50.2730)	(5.8980)	(−2.6032)			(50.1269)	(5.6937)	(−2.1349)	(−2.1084)	(−0.0661)	(−0.4382)	(−2.3589)	
4	1.5653***	0.1965***	−0.0138***	0.10	4	1.5691***	0.1907***	−0.0119***	−0.0048*	−0.0000	−0.1876	−0.3449**	0.10
	(49.6841)	(6.4621)	(−3.1830)			(49.5821)	(6.2305)	(−2.7459)	(−1.7107)	(−0.0087)	(−0.8147)	(−2.4282)	
5 (Largest)	1.4890***	0.2314***	−0.0123***	0.15	5 (Largest)	1.4951***	0.2221***	−0.0098**	−0.0094**	0.0030	−0.5104	−0.3350**	0.16
	(45.3147)	(7.8231)	(−2.8785)			(45.9838)	(7.7653)	(−2.2380)	(−2.4559)	(0.8298)	(−1.2403)	(−2.1907)	
Up market					Up market								
1 (Smallest)	1.4967***	0.0555**	−0.0079**	0.00	1 (Smallest)	1.4995***	0.0527**	−0.0066*	−0.0097	0.0143*	−0.0666	0.4889	0.01
	(61.0092)	(2.5027)	(−2.1918)			(61.0195)	(2.3651)	(−1.6660)	(−1.5555)	(1.7384)	(−0.1467)	(1.2812)	
2	1.5446***	0.0734***	−0.0119***	0.01	2	1.5468***	0.0711***	−0.0110***	−0.0080	0.0096	−0.0778	0.3957	0.01
	(63.6554)	(3.3487)	(−3.3167)			(63.5729)	(3.2218)	(−2.8083)	(−1.4188)	(1.2065)	(−0.2769)	(1.0389)	
3	1.5641***	0.1043***	−0.0161***	0.01	3	1.5663***	0.1019***	−0.0149***	−0.0091	0.0088	−0.0791	0.3062	0.01
	(62.5662)	(4.6188)	(−4.3640)			(62.4758)	(4.4784)	(−3.7086)	(−1.5745)	(1.0717)	(−0.2732)	(0.7802)	
4	1.5632***	0.1390***	−0.0200***	0.02	4	1.5657***	0.1360***	−0.0191***	−0.0073	0.0078	−0.1871	0.2130	0.02
	(62.3408)	(6.1365)	(−5.4096)			(62.2374)	(5.9570)	(−4.7250)	(−1.2514)	(0.9549)	(−0.6438)	(0.5410)	
5(Largest)	1.4825***	0.2191***	−0.0236***	0.06	5 (Largest)	1.4848***	0.2159***	−0.0222***	−0.0094	0.0052	−0.1667	0.0160	0.06
	(54.9549)	(8.9867)	(−5.9310)			(54.8561)	(8.7928)	(−5.1048)	(−1.5085)	(0.5836)	(−0.5331)	(0.0377)	
Down market					Down market								
1 (Smallest)	1.5323***	0.3319***	−0.0270***	0.26	1 (Smallest)	1.5380***	0.3236***	−0.0248***	−0.0040	0.0018	−0.2967	−0.3792**	0.26
	(55.4405)	(14.9825)	(−9.5049)			(55.6406)	(14.5082)	(−8.3215)	(−1.3751)	(0.5409)	(−1.1353)	(−2.4828)	
2	1.5761***	0.3378***	−0.0280***	0.27	2	1.5822***	0.3289***	−0.0260***	−0.0035	−0.0014	−0.2577	−0.3722**	0.27
	(58.2103)	(15.5659)	(−10.0540)			(58.4210)	(15.0520)	(−8.8951)	(−1.2186)	(−0.4318)	(−1.0065)	(−2.4871)	
3	1.5939***	0.3364***	−0.0278***	0.24	3	1.6007***	0.3265***	−0.0254***	−0.0068**	0.0005	−0.3920	−0.3478**	0.25
	(55.2919)	(14.5564)	(−9.3596)			(55.5669)	(14.0457)	(−8.1532)	(−2.2254)	(0.1442)	(−1.4395)	(−2.1849)	
4	1.5689***	0.3310***	−0.0270***	0.24	4	1.5759***	0.3207***	−0.0246***	−0.0061*	0.0005	−0.4074	−0.3791**	0.24
	(53.6283)	(14.1131)	(−8.9719)			(53.9067)	(13.5964)	(−7.7934)	(−1.9591)	(0.1576)	(−1.4741)	(−2.3469)	
5 (Largest)	1.4811***	0.3125***	−0.0188***	0.25	5 (Largest)	1.4909***	0.2982***	−0.0160***	−0.0111***	0.0042	−0.9516***	−0.3582**	0.27
	(44.3711)	(11.6811)	(−5.4717)			(44.9170)	(11.1330)	(−4.4537)	(−3.1521)	(1.0679)	(−3.0326)	(−1.9529)	

Note: Panels A and B of this table report the regressions results of Eqs. (3) and (4), respectively, for size-based quintile portfolios for the full sample, up markets, and down markets; portfolios are constructed based on month-end market capitalization. The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. $\overline{R}^2$ is the adjusted R^2.

*** Represents statistical significance at the 1% level.

** Represents statistical significance at the 5% level.

* Represents statistical significance at the 10% level.

smallest portfolios. These results reflect that large stocks generally have high trading volumes and high total debt ratio such that they respond intensively to interest rate increase. Moreover, the coefficient of γ_4 in the smallest portfolio is significantly positive in up markets, whereas γ_5 in the largest portfolio is significantly negative in down markets. As stated earlier, these results suggest that interest rate decrease and CNY appreciation as good news to the Chinese stock market will amplify herding in up markets but will weaken it in down markets.

Table 4 reports the regression results of portfolios sorted by BTM values. The lowest and highest BTM value portfolios are characterized as growth stocks and value stocks, respectively (Fama & French, 1993). Panel A of Table 4 indicates that herding patterns are observed across different BTM quintile portfolios for the full sample, up markets, and down markets since herding coefficients γ_2 are all significantly negative. The results suggest that investors exhibit a higher level of herding in growth stocks ($\gamma_2 = -0.0117$) than in value stocks ($\gamma_2 = -0.0090$) for the full sample. In addition, herding level decreases monotonically from the lowest BTM portfolio to the highest BTM portfolio in up markets, whereas the lowest and highest BTM portfolios exhibit a weaker herding level compared with the 2nd, 3rd, and 4th portfolios in down markets. In general, the high herding level of growth stocks may be attributed to increased difficulty in measuring the intrinsic value of these stocks and that growth stock prices are influenced more by investor behavior rather than by fundamental valuation. With regard to the influence of variations in interest and exchange rates on herding, Panel B shows that for the full sample, CNY depreciation leads to herding across different BTM quintile portfolios. By contrast, interest rate increase has no effect on herding in the two lowest BTM quintiles. Fama and French (1992) point out that low BTM firms are persistently strong performers, whereas high BTM firms are persistently weak performers. Thus, value stocks are likely to be financially constrained and confronted with high external financing costs and even credit rationing. Consequently, value stocks are more sensitive to interest rate variations than growth stocks. Moreover, we find that interest rate increase and CNY depreciation will amplify herding across different BTM portfolios in down markets. However, this case does not hold in up markets. Interestingly, the significantly negative γ_5 in the two lowest BTM quintiles in down markets reflect that good news in down days increases the divergence of opinions of investors and weakens herding in the stock market.

4.3. Idiosyncratic volatility and intentional herding

We aim to detect intentional herding by comparing herding patterns in different IVOL portfolios. Panel A of Table 5 shows that the herding level of the highest IVOL quintile portfolio ($\gamma_2 = -0.0124$) is twice that of the lowest quintile portfolio ($\gamma_2 = -0.0057$), thereby suggesting that intentional herding occurs in the Chinese stock market. Panel B shows that interest rate increase and CNY depreciation significantly affect herding behavior in the first four IVOL quintiles, whereas the highest IVOL quintile remains unaffected.

Table 4
Regression results of the daily $CSAD_t$ for portfolios sorted by BTM value.

Sample	α	γ_1	γ_2	$\bar{R}^2$	Sample	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	$\bar{R}^2$
Panel A: regressions results based on Eq. (3)					Panel B: regressions results based on Eq. (4)								
Full sample					Full sample								
1 (Lowest)	1.8652***	0.2040***	−0.0117**	0.10	1 (Lowest)	1.8689***	0.1985***	−0.0097*	−0.0049	0.0033	−0.2380	−0.3184**	0.10
	(52.4036)	(5.9254)	(−2.3513)			(52.4159)	(5.7518)	(−1.9485)	(−1.5057)	(0.6664)	(−0.8224)	(−1.9736)	
2	1.6677***	0.2032***	−0.0134***	0.10	2	1.6715***	0.1974***	−0.0119***	−0.0038	−0.0013	−0.2298	−0.3171**	0.10
	(51.6486)	(6.3320)	(−2.9152)			(51.6493)	(6.1406)	(−2.5990)	(−1.2940)	(−0.2753)	(−0.8877)	(−2.2175)	
3	1.5282***	0.1870***	−0.0120***	0.10	3	1.5320***	0.1813***	−0.0098**	−0.0065**	0.0006	−0.1353	−0.3455***	0.10
	(50.0176)	(6.3443)	(−2.8638)			(50.0593)	(6.1758)	(−2.3219)	(−2.3528)	(0.1522)	(−0.5166)	(−2.7060)	
4	1.3951***	0.1749***	−0.0110***	0.10	4	1.3986***	0.1697***	−0.0089**	−0.0053*	0.0000	−0.0918	−0.3657***	0.10
	(48.1761)	(6.2844)	(−2.7531)			(48.0797)	(6.0771)	(−2.2037)	(−1.8816)	(0.0061)	(−0.3566)	(−2.9019)	
5 (Highest)	1.2144***	0.1727***	−0.0090***	0.12	5 (Highest)	1.2183***	0.1669***	−0.0068*	−0.0070***	−0.0002	−0.1574	−0.3138***	0.13
	(43.4808)	(7.0513)	(−2.5959)			(43.6296)	(6.8821)	(−1.9381)	(−2.6891)	(−0.0498)	(−0.5247)	(−2.8778)	
Up market					Up market								
1 (Lowest)	1.8250***	0.1732***	−0.0232***	0.03	1 (Lowest)	1.8281***	0.1699***	−0.0217***	−0.0096	0.0137	−0.1359	0.3525	0.03
	(61.6126)	(6.4720)	(−5.3127)			(61.5462)	(6.3043)	(−4.5557)	(−1.3988)	(1.4168)	(−0.3960)	(0.7582)	
2	1.6637***	0.1270***	−0.0179***	0.02	2	1.6664***	0.1237***	−0.0166***	−0.0088	0.0090	−0.1745	0.2102	0.02
	(63.9369)	(5.4001)	(−4.6488)			(63.8448)	(5.2230)	(−3.9585)	(−1.4646)	(1.0568)	(−0.5788)	(0.5146)	
3	1.5291***	0.1041***	−0.0157***	0.01	3	1.5314***	0.1014***	−0.0142***	−0.0098	0.0080	−0.0997	0.2015	0.01
	(63.1942)	(4.7614)	(−4.3856)			(63.1076)	(4.6044)	(−3.6612)	(−1.5338)	(1.0078)	(−0.3556)	(0.5305)	
4	1.3969***	0.0972***	−0.0142***	0.01	4	1.3988***	0.0953***	−0.0131***	−0.0082	0.0092	−0.0293	0.3343	0.01
	(60.4092)	(4.6537)	(−4.1698)			(60.3300)	(4.5301)	(−3.5290)	(−1.5410)	(1.2169)	(−0.1093)	(0.9211)	
5 (Highest)	1.2231***	0.1082***	−0.0119***	0.02	5 (Highest)	1.2250***	0.1060***	−0.0109***	−0.0078	0.0063	−0.0848	0.2135	0.02
	(54.9038)	(5.3739)	(−3.6207)			(54.8155)	(5.2271)	(−3.0411)	(−1.5087)	(0.8711)	(−0.3284)	(0.6103)	
Down market					Down market								
1 (Lowest)	1.9097***	0.3232***	−0.0230***	0.22	1 (Lowest)	1.9167***	0.3130***	−0.0206***	−0.0059***	0.0036	−0.5621**	−0.3756***	0.22
	(40.4436)	(7.4946)	(−3.9493)			(40.7034)	(7.3843)	(−3.4165)	(−2.7585)	(1.6382)	(−2.3157)	(−2.6047)	
2	1.6811***	0.3620***	−0.0297***	0.26	2	1.6881***	0.3517***	−0.0279***	−0.0046**	−0.0006	−0.5161**	−0.3278***	0.26
	(40.8291)	(9.1297)	(−5.7021)			(41.2810)	(9.0804)	(−5.2928)	(−2.2321)	(−0.3289)	(−2.1408)	(−2.8404)	
3	1.5371***	0.3524***	−0.0291***	0.28	3	1.5440***	0.3425***	−0.0265***	−0.0077***	0.0017	−0.4163	−0.3536***	0.28
	(38.7580)	(9.6363)	(−6.0068)			(39.1059)	(9.5820)	(−5.3357)	(−3.9118)	(0.9482)	(−1.6386)	(−3.3865)	
4	1.4022***	0.3293***	−0.0269***	0.27	4	1.4094***	0.3189***	−0.0243***	−0.0064***	0.0007	−0.3868	−0.4004***	0.28
	(37.2962)	(9.5609)	(−5.8781)			(37.6592)	(9.4910)	(−5.1431)	(−3.2931)	(0.2893)	(−1.2819)	(−4.1197)	
5 (Highest)	1.2094***	0.3012***	−0.0220***	0.26	5 (Highest)	1.2166***	0.2909***	−0.0194***	−0.0084***	0.0005	−0.4115	−0.3369***	0.27
	(31.2627)	(9.1071)	(−4.9650)			(31.7587)	(9.1222)	(−4.1375)	(−3.8140)	(0.2292)	(−0.9000)	(−3.1793)	

Note: Panels A and B of this table report the regressions results of Eqs. (3) and (4), respectively, for BTM-based quintile portfolios for the full sample, up markets, and down markets; portfolios are constructed based on month-end BTM values in which stocks with negative BTM values are eliminated. The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. $\bar{R}^2$ is the adjusted R^2.

*** Represents statistical significance at the 1% level.
** Represents statistical significance at the 5% level.
* Represents statistical significance at the 10% level.

Then the following questions remain: what are the characteristics of different IVOL stocks and what drives high herding level in high IVOL stocks? Table 6 provides a clear picture of the composition of IVOL quintile portfolios. Specifically, this table reports the average across the months in the sample of the mean values within each month of various characteristics for the stock in each IVOL quintile portfolio. The characteristic variables include market capitalization (in billions of CNY), BTM ratio, volume (in billions of shares), systematic volatility (annualized in percentage), skewness, institutional ownership (in percentage), and number of institutions.[1]

The results in Table 6 exhibit interesting patterns. First, market capitalization and BTM ratio decrease monotonically as IVOL increases across quintiles, indicating that the highest IVOL stocks are generally small growth stocks. Second, the lowest and highest IVOL stocks have high trading volume, and systematic volatility increases monotonically as IVOL increases. Third, the monotonic increase in skewness as IVOL increases suggests that the highest IVOL stocks are attractive to investors who have skewness preference (Bali, Cakici & Whitelaw, 2011) because these stocks have a small probability of a large gain. Finally, regardless of whether measured by institutional ownership or number of institutions, institutions exhibit a relative aversion for the highest IVOL stocks; that is, retail investors strongly prefer this type of stocks.

Subsequently, we investigate the cause of the high herding level in high IVOL stocks as shown in Table 5. We form IVOL portfolios controlling for the aforementioned characteristics and reexamine the herding level in these portfolios. For example, we form IVOL portfolios controlling for size by first forming quintile portfolios sorted by size every month. Then, in each size portfolio, we sort stocks into quintile portfolios ranked based on IVOL so that quintile 1 has the lowest IVOL stocks, whereas quintile 5 has the highest IVOL stocks. Finally, we reconstitute the quintile portfolios by sorting quintile k ($k = 1,2,3,4,5$) in each size portfolio into one quintile, thereby forming the IVOL quintile portfolios controlling for size.

Table 7 reports the herding coefficients based on Eq. (3) sorted by IVOL after controlling for various characteristics. The results show that after controlling for size, BTM ratio, volume and skewness, the herding level changes slightly compared with the no control group. Therefore, these characteristics may not be the cause of the high herding level among the highest IVOL stocks. Moreover, we still find that the herding level of the highest IVOL quintile portfolio is twice that of the lowest quintile portfolio after controlling for systematic volatility, indicating that the high herding level in the highest IVOL quintile portfolio does not arise from systematic risks in the stock market. The most impressive results in Table 7 are obtained after controlling for institutional ownership or number of institutions. The herding levels of the two highest quintile portfolios weaken, whereas the herding levels of the two lowest quintile portfolios strengthen. Therefore, retail investors play an important role in amplifying the herding among the highest IVOL stocks. This

[1] Skewness is the measure of the third central moment of returns; systematic volatility is calculated as the standard deviation of estimated systematic returns according to Eq. (8).

Table 5
Regression results of the daily $CSAD_t$ for portfolios sorted by IVOL.

Sample	α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	$\overline{R}^2$
Panel A: regressions results based on Eq. (3)								
1 (Lowest)	0.8726***	0.1628***	−0.0057*					0.20
	(37.8940)	(7.6736)	(−1.8602)					
2	1.1607***	0.1736***	−0.0089**					0.14
	(43.7142)	(6.8189)	(−2.3994)					
3	1.4058***	0.1995***	−0.0136***					0.12
	(47.6226)	(7.1492)	(−3.3981)					
4	1.7174***	0.2095***	−0.0162***					0.09
	(51.6220)	(6.7014)	(−3.5889)					
5 (Highest)	2.4389***	0.1851***	−0.0124**					0.05
	(58.7092)	(4.7828)	(−2.2974)					
Panel B: regressions results based on Eq. (4)								
1 (Lowest)	0.8764***	0.1572***	−0.0038	−0.0065***	0.0024	−0.2625	−0.2584**	0.20
	(38.1935)	(7.5289)	(−1.2121)	(−2.8364)	(0.8894)	(−0.9474)	(−2.5449)	
2	1.1651***	0.1670***	−0.0073*	−0.0051**	0.0004	−0.3589	−0.2957**	0.14
	(44.0529)	(6.6414)	(−1.9566)	(−2.0076)	(0.1178)	(−1.3732)	(−2.5092)	
3	1.4099***	0.1935***	−0.0121***	−0.0048*	0.0007	−0.3123	−0.2903*	0.12
	(47.7518)	(6.9531)	(−2.9858)	(−1.8583)	(0.1755)	(−1.2599)	(−1.9178)	
4	1.7221***	0.2025***	−0.0141***	−0.0057**	0.0002	−0.2920	−0.3859**	0.09
	(51.7307)	(6.5248)	(−3.1488)	(−1.9894)	(0.0392)	(−1.0887)	(−2.5285)	
5 (Highest)	2.4432***	0.1785***	−0.0113**	−0.0044	−0.0021	−0.4047	−0.2291	0.05
	(58.5772)	(4.5817)	(−2.0896)	(−1.0252)	(−0.3045)	(−1.0733)	(−1.4430)	

Note: Panels A and B of this table report the regressions results of Eqs. (3) and (4), respectively, for IVOL-based quintile portfolios; portfolios are constructed based on Eq. (8) each month. The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. $\overline{R}^2$ is the adjusted R^2.
*** Represents statistical significance at the 1% level.
** Represents statistical significance at the 5% level.
* Represents statistical significance at the 10% level.

finding is consistent with previous studies, which indicate that retail investors demonstrate gambling propensity in the stock market. Kumar (2009) argues that certain groups of retail investors exhibit preference for lottery-type stocks, which he defines as low-priced stocks with high IVOL and high idiosyncratic skewness. He further argues that the gambling preferences of retail investors are reflected in their stock investment decisions. Foucault, Sraer, and Thesmar (2011) find that retail trading endogenously has a positive causal effect on IVOL, suggesting that retail investors behave as noise traders. Kumar, Page, and Spalt (2016) report that correlated trading by gambling-motivated investors generates excess return co-movement among lottery-type stocks. In summary, stocks with high IVOL are attractive to investors, particularly among retail investors. Therefore, high IVOL stocks may trigger irrational behavior among retail investors, particularly under market stress. Consequently, a high herding level occurs in the highest IVOL quintile.

4.4. Monetary policy announcements and extreme exchange rate volatility

Panel A of Table 8 reports the effects of monetary policy announcements on investor behavior. The empirical results show that after a contractionary monetary policy shock, an announcement of raising the benchmark deposit rate leads to herding behavior since ω_1 is significantly negative, whereas an increase in the deposit reserve ratio does not lead to herding. By contrast, after an easy monetary policy shock (cutting the benchmark deposit rate or cutting the deposit reserve ratio), the aggregate market displays "anti-herding" behavior since ω_3 and ω_4 are both significantly positive and higher than the absolute value of γ_2. Panel B shows that the extreme 1% CNY appreciation level does not induce herding, whereas the 1% CNY depreciation level significantly leads to herding. This result is consistent with the early finding that local currency depreciation is considered bad news for emerging markets, thereby reducing the attractiveness of the stock market and triggering intensive response by investors.

5. Conclusion

Interest and exchange rates are two important macroeconomic variables that considerably affect the stock returns. In this study, we examine whether variations in interest and exchange rates induce investors' tendency to herd in the Chinese stock market.

Our results show that interest rate increase and CNY depreciation will induce herding behavior. This phenomenon is mainly manifested

Table 6
Summary statistics for quintile portfolios of stocks sorted by IVOL.

Quintile	IVOL	Size	BTM ratio	Volume	SVOL	Skewness	IO	NI
Lowest	17.0504	29.3110	0.4748	0.2438	32.7937	0.2202	31.6574	21
2	24.0289	12.2750	0.3699	0.1951	34.8246	0.3110	30.9123	19
3	29.7396	9.9150	0.3196	0.1901	35.7935	0.3710	31.0619	19
4	36.6626	8.7250	0.2872	0.2048	36.9732	0.4465	30.4474	18
Highest	51.0285	7.2370	0.2557	0.2437	38.6931	0.4689	28.1900	15

Note: This table reports the average across the months in the sample of the mean values within each month of various characteristics for the stock in each IVOL quintile portfolio. The characteristic variables include IVOL (annualized in percentage), market capitalization (in billions of CNY), BTM ratio, volume (in billions of shares), systematic volatility (SVOL, annualized in percentage), skewness, institutional ownership (IO, in percentage) and number of institutions (NI).

Table 7
Herding coefficients of quintile portfolios sorted by IVOL after controlling for various stock characteristics.

	Ranking on IVOL				
	1 (Lowest)	2	3	4	5 (Highest)
No control	−0.0057*	−0.0089**	−0.0136***	−0.0162***	−0.0124**
	(−1.8602)	(−2.3994)	(−3.3981)	(−3.5889)	(−2.2974)
Controlling for size	−0.0057*	−0.0091**	−0.0138***	−0.0163***	−0.0120**
	(−1.8601)	(−2.4368)	(−3.3771)	(−3.6550)	(−2.2476)
Controlling for book-to-market	−0.0066**	−0.0095***	−0.0134***	−0.0159***	−0.0114**
	(−2.0111)	(−2.6507)	(−3.3456)	(−3.5964)	(−2.1685)
Controlling for volume	−0.0062**	−0.0088**	−0.0138***	−0.0161***	−0.0120**
	(−2.0106)	(−2.3627)	(−3.4574)	(−3.5478)	(−2.2605)
Controlling for systematic volatility	−0.0054*	−0.0090**	−0.0127***	−0.0145***	−0.0134**
	(−1.7209)	(−2.5726)	(−3.4065)	(−3.4528)	(−2.4162)
Controlling for skewness	−0.0058*	−0.0084**	−0.0133***	−0.0163***	−0.0129**
	(−1.8946)	(−2.3089)	(−3.3282)	(−3.5586)	(−2.4076)
Controlling for institutional ownership	−0.0065**	−0.0110***	−0.0136***	−0.0150***	−0.0107**
	(−2.0502)	(−3.0357)	(−3.2646)	(−3.4058)	(−2.0652)
Controlling for numbers of institutions	−0.0064**	−0.0112***	−0.0141***	−0.0149***	−0.0103***
	(−2.0454)	(−3.1094)	(−3.3957)	(−3.3822)	(−1.9407)

Note: This table reports the herding coefficients based on Eq. (3) sorted by IVOL after controlling for market capitalization, BTM ratio, volume, systematic volatility, skewness, institutional ownership and number of institutions. The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

in down markets, which reflects that investors respond more intensively to bad news than to good news. Furthermore, we propose a novel method to detect the occurrence of intentional herding by examining whether investors herd on the idiosyncratic risk of stocks. We find that the herding level of the highest IVOL quintile portfolio is twice that of the lowest quintile portfolio, thereby proving that intentional herding occurs in the Chinese stock market. This finding is consistent with the prediction that retail investors prefer lottery-type stocks in which high IVOL is one of the most remarkable characteristics, and that retail investors tend to overweigh considerably and heavily trade such stocks (Kumar, 2009; Han & Kumar, 2013). Finally, we investigate the effects of monetary policy announcements and extreme exchange rate volatility on herding.

The findings in this study present important implications for practitioners and policymakers. First, the results may help improve understanding of the sources of co-movement in stock returns. The traditional view considers that co-movement in stock returns are mainly attributed to correlated cash flows and systematic shifts in discount rates (Kumar et al., 2016). Spurious herding reflects such systematic effects to a certain extent. However, the occurrence of intentional herding in this study suggests that the non-standard preferences of investors may be an important cause of correlated trading. Second, institutional investors require a larger number of securities to achieve the same degree of diversification, particularly when macro information undergoes considerable change. Finally, policymakers should strengthen communications with financial markets and manage the expectations of fluctuations in policy because macro information change may lead to herding in the aggregate market. Future research can examine other macro information on herding and further distinguish between spurious herding and intentional herding in the stock market.

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Table 8
Regression results of the daily $CSAD_t$ under monetary policy announcements and extreme exchange rate volatility.

Sample	α	γ_1	γ_2	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	$\overline{R}^2$
Panel A: regression results under monetary policy announcements										
	1.5363***	0.1862***	−0.0111***	−0.0151*						0.11
(1)	(50.6384)	(6.4120)	(−2.6761)	(−1.6681)						
	1.5368***	0.1854***	−0.0110***		−0.0024					0.11
(2)	(50.6154)	(6.3779)	(−2.6246)		(−0.8198)					
	1.5366***	0.1863***	−0.0115***			0.0190**				0.11
(3)	(50.8720)	(6.4803)	(−2.7704)			(2.0773)				
	1.5363***	0.1867***	−0.0115***				0.0210**			0.11
(4)	(50.8445)	(6.4794)	(−2.7806)				(2.0463)			
Panel B: regression results under extreme exchange rate volatility										
	1.5369***	0.1853***	−0.0110***					0.0029		0.11
(5)	(50.6863)	(6.3942)	(−2.6656)					(0.3775)		
	1.5379***	0.1838***	−0.0106**						−0.0089**	0.11
(6)	(50.5115)	(6.3113)	(−2.5372)						(−2.5031)	

Note: Panels A and B of this table report the regressions results of Eq. (9), where Dum_1 to Dum_4 denote the dummy variables that take the value of one a day after the central bank raises the benchmark deposit rate, raises the deposit reserve ratio, cuts the benchmark deposit rate, cuts the deposit reserve ratio respectively and zero otherwise. In addition, Dum_5 takes the value of one on a day when Δex_t lies in the extreme 1% lower tail of the entire Δex_t distribution (appreciation), whereas Dum_6 is one when Δex_t lies in the extreme 1% upper tail of the entire Δex_t distribution (depreciation). The numbers in the parentheses are t-statistics based on Newey and West's (1987) heteroscedasticity and autocorrelation consistent standard errors. $\overline{R}^2$ is the adjusted R^2.

*** Represents statistical significance at the 1% level.
** Represents statistical significance at the 5% level.
* Represents statistical significance at the 10% level.

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