Finance Research Letters 23 (2017) 121–132

Contents lists available at ScienceDirect

Finance Research Letters

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

Herding effect on idiosyncratic volatility in U.S. industries

Ahmed BenSaïda

LaREMFiQ – IHEC, Sousse University, B.P. 40 Sahloul 3, Sousse 4054, Tunisia

A R T I C L E I N F O

Article history:
Received 20 January 2017
Accepted 8 March 2017
Available online 9 March 2017

JEL classification:
G14
G15
C22

Keywords:
Herding
Turmoil
Volume turnover
Investor sentiment
Conditional volatility

A B S T R A C T

This paper investigates the effect of herding behavior on excessive market idiosyncratic volatility in the U.S. stock market at a sectoral level. We carefully modify the cross sectional absolute deviation model to include trading volume and investors' sentiment as herding triggers, and show that herding is indeed present in almost every sector of the U.S. stock market during turmoil periods. Furthermore, our particularly designed GJR-GARCH model provides new insights on the effect of herding and volume turnover on the conditional volatility. The sample covers all listed companies in the American stock market over four major turmoil periods.

1. Introduction

Herding in financial markets has been the center of considerable attention from researchers in recent years. Indeed, when classical financial theories fail to explain asset price movement, researchers are prone to find answers in behavioral finance (Babalos et al., 2015). As argued by Litimi et al. (2016), behavioral theory assumes that excessive market volatility is derived from volatile emotions and beliefs of the investors, and exists as long as they express erroneous and psychological pitfalls.

The literature dealing with herding is divided in two categories. On one hand, some studies examine herding behavior among institutional investors, such as mutual fund managers and financial analysts, and require detailed data on every transaction effected by these investors (Lakonishok et al., 1992; Nofsinger and Sias, 1999). On the other hand, most studies on the existence of herding investigate the shifts in stock returns' dispersion, since the data can be easily collected (Babalos et al., 2015; Litimi et al., 2016).

Studies on herd behavior are widely applied to global indexes, and only few researches focus on sector herding (Christie and Huang, 1995; Choi and Sias, 2009; Litimi et al., 2016). However, this behavior may affect only some sectors due to sector-styles, the quality of investors operating in each sector … etc. In fact, Henker et al. (2006) find that herding is more prevalent in industries such as materials, consumer staples and financials. Gebka and Wohar (2013) find that sectors such as basic materials, consumer services, and oil and gas reveal herding behavior more than other sectors. They advance that this pattern may be driven by a group of investors that follow each other in and out of markets, overconfidence, or excessive

E-mail address: ahmedbensaida@yahoo.com

http://dx.doi.org/10.1016/j.frl.2017.03.001
1544-6123/

flight to quality. Moreover, in the Malaysian context, Dehghani and Sapian (2014) find that herding behavior is only constrained to technology sector. Litimi et al. (2016) test a modified version of Chang et al. (2000) measure while including trading volume and investor sentiment; they find that in 6 sectors out of 12 (consumer non-durables, energy, health care, public utilities, technology, and transportation), the sector return generates herding during financial bubbles and crises. Dealing with herding around the overall market can be misleading, since the existing literature emphasizes the importance of industry classification on herd behavior. As argued by Gebka and Wohar (2013), herding is absent when focusing on world-wide markets; yet, when different economic sectors are considered separately, herding behavior is detected in some sectors.

Furthermore, herding behavior causes prices deviation from their fundamental values and may trigger excess volatility (Dennis and Strickland, 2002; Gabaix et al., 2006). From this perspective, a substantial body of literature treating herding behavior and volatility has been documented. Holmes et al. (2013) find that intentional herding is more prevalent during low volatility periods. Ben Mabrouk and Fakhfekh (2013) find that herding behavior is asymmetric to market turns. They employed an EGARCH model to capture herding asymmetry. Blasco et al. (2012); Balcilar et al. (2014); and Huang et al. (2015) provide empirical investigation between herding movement and idiosyncratic conditional volatility and find that herding behavior boosts market volatility. Technically, these results are consistent with the GARCH specification.

Another branch of literature aims at studying herding behavior during markets turmoil. In fact, Demirer et al. (2010) find evidence of herding during market downturns in the Taiwanese context, when considering both the overall market and each sector separately. In the Chinese Market, Tan et al. (2008) inspect herd behavior in A and B stocks, and find that herding is more pronounced in the former during upturns. Chiang and Zheng (2010) use a sample of 18 countries around the world and find that herding is more likely to occur in advanced and Asian markets, especially during downturns. However, no herding is reported in Latin America countries. Besides, they find that herding is more evident during crisis periods. Economou et al. (2011) study herding behavior in several European countries. They find evidence of herding in the U.S., Portugal, and Italian markets, whereas no herding in Greece and Spain during the recent crisis. They also find that herding is apparent in Greece only in up markets and it is correlated across countries. These mixed results suggest that crisis periods and market movements (bullish or bearish) seem to be pertinent (Evans and Borders, 2014; Hausman and Johnston, 2014), even though their real impact on herding is ambiguous.

In addition, several researchers (Chuang and Lee, 2006; Tan et al., 2008; Litimi et al., 2016) find that trading volume fuels herding behavior. In fact, trading volume is generated by overconfidence, which implies high volatility. Meanwhile, if investors herd around the market consensus, prices will deviate from their equilibrium values, which stimulate trading volume and hence, volatility. So, the linkage between herding, volatility and trading volume is straightforward.

In this context, our study is an important contribution to recent literature which tests the effect of herding on idiosyncratic volatility in a sectorial context, rather than the general overall U.S. stock market. Moreover, our study fills up the gap in the literature on herding behavior and its relationship with trading volume and investor sentiment, and examines more deeply the impact of this cross relationships on idiosyncratic volatility during crisis and normal periods.

Still, very few studies empirically investigate the effect of herding movement on idiosyncratic conditional volatility in the U.S. market. Several attempts have been conducted in this domain using unconditional volatility, including Blasco et al. (2012) in the Spanish stock market, Balcilar et al. (2014) in the Gulf Arab stock markets, Huang et al. (2015) in Taiwan equity market, and Boubaker et al. (2015) in the Egyptian stock market. The lack of literature on the effect of herding on idiosyncratic volatility has motivated us to examine this issue more deeply for the various sectors of the market rather than the general overall U.S. stock market. The remainder of this paper is organized as follows: Section 2 describes the methodology; Section 3 presents the data and discusses the results; finally, we conclude in Section 4.

2. Methodology

Behavioral finance literature has provided several models to measure herding behavior based on the type of investors under consideration, *i.e.*, institutional or individual, and the theoretical background that explains herding co-movement. The study of herding among institutional investors needs very detailed data on each transaction of that group of investors, and it generally suffers from infrequent observations and misidentification of the concerned traders (Kremer and Nautz, 2013). And the study of herding among retail investors necessitates the same type of data as for institutional ones, namely transaction or portfolio data. Alternatively, there is no universal model to test the presence of herding among individual investors due to the variety of empirical designs across studies (Yao et al., 2014; Litimi et al., 2016).

We differentiate between two main empirical model lineages based on aggregate data that investigate investors herd behavior, models based on returns dispersion (Christie and Huang, 1995; Chang et al., 2000), and state-space models based on macro factors (Hwang and Salmon, 2004; Xie et al., 2015). The major handicap of state-space models is that they perform a tradeoff between beta-estimation and maintaining a sufficient number of observations to plot herding. Consequently, the frequency of the collected data is reduced, *e.g.*, from daily to monthly, in order to compute the standard deviation of the biased systematic risk inferred from the capital asset pricing model (CAPM); and since the dynamics of stock markets are constantly and rapidly evolving, measuring herding at lower frequencies provides little information, and is inadequate to explain the excessive market heteroscedastic volatility. For example, the Huang and Salmon (2004) measure is based on the cross-sectional dispersion of the factor sensitivity of assets within a given market. The starting point of this measure is the Capital Asset Pricing Model (hereafter CAPM). According to Hwang and Salmon (2004), if herding is present, the cross-sectional dispersion of the betas would be lower. So, in the presence of herding, the linear relationship between the returns and the beta will be biased and no longer holds. Hence, the dispersions of individual betas will be smaller than it would be in equilibrium. If securities returns were expected to be equal to the market return, then the cross-sectional variance would be zero. The validity of the Huang and Salmon (2004) measure is conditioned to the validity of the CAPM which is based on various restricted assumptions (efficiency market hypothesis, rational expectations, … etc.).

Recently, Xie et al. (2015) develop a new method based on Arbitrage Pricing Theory to test herding behavior. Their measure supposes that stocks' returns are sufficiently explained by factors in APT model. However, the literature on APT does not provide any consensus on the number of factors included.

Alternatively, in the returns dispersion based models, Christie and Huang (1995) and Chang et al. (2000) have introduced the cross sectional standard deviation (CSSD) and the cross sectional absolute deviation (CSAD), respectively. The CSSD is more susceptible to the effect of outliers, as mentioned by Economou et al. (2011). Therefore, we select the CSAD measure of Chang et al. (2000) to perform our analysis, since numerous researchers have confirmed its superiority over the CSSD based model (Yao et al., 2014; BenSaïda et al., 2015; Litimi et al., 2016). The performance of the CSAD model hinges on several factors: first, because the CSSD model is linear, whereas herding entails nonlinearities (Lux, 1995); second, because Christie and Huang (1995) test for herding during market extremes, ignoring non extreme periods that may well also accommodate herding; yet, the definition of extreme movements employed by the authors is rudimentary and arbitrary.

2.1. CSAD herding model

Rational financial theory assumes a positive linear relationship between the stock returns dispersion and the average market return. However, if investors imitate each other and act in conformity with the general market consensus, then individual stock returns would not deviate significantly from the market return. Chang et al. (2000) have suggested the CSAD as a herding indicator inspired from the CAPM, since it measures the average proximity of individual returns to the mean return, it reveals the presence of herd behavior (Christie and Huang, 1995, p. 36). Herding is reflected by the negative relationship between the CSAD measure and the average return squared. When an investor adopts the group's behavior, the divergence in the dispersion of stock returns from the mean value should be very small, if not null. The CSAD is expressed as follows:

$$CSAD_t = \frac{1}{N_t}\sum_{i=1}^{N_t}|R_{i,t} - R_{m,t}|$$

Where:

$R_{i,t}$ is the observed stock return of company i at time t;

$R_{m,t}$ is the average of the returns of the sector portfolio's constituent stocks at time t in the stock market and is computed for each sector by including only sector specific stocks. We choose the equally-weighted-average of the market return for practical considerations, since Tan et al. (2008) report no difference between the weighted-average and the equally-weighted-average of the market return.

If the investors are rational and estimate the price in accordance with the CAPM model, then the relationship between CSAD and $R_{m,\,t}$ should be linear and increasingly positive. However, if the investors herd around the market, the path of the stock return converges towards the average market trend. Consequently, the relationship between CSAD and the average market return $R_{m,\,t}$ becomes nonlinear and negative (Chang et al., 2000; Henker et al., 2006). The nonlinearity is captured by $R^2_{m,t}$, and is expressed in Eq. (1).

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t \tag{1}$$

If herding is present, γ_2 is expected to be significantly negative (Economou et al., 2011).

2.2. The modified CSAD herding model

Karpoff (1987) explains that trading volume and price fluctuations are positively related. Moreover, Chuang and Lee (2006) and Tan et al. (2008) report that trading volume might enhance herding, and therefore high volatility. As argued by Litimi et al. (2016), market investors bypass their trading strategies to imitate presumably well informed traders during turmoil periods to avoid large losses. Consequently, we assume that trading volume may be a vital element in fueling herding.

Hwang and Salmon (2004) suggest that investors sentiment might be an important factor in fueling herd behavior. In fact, an investor – faced by fear of brutal market fluctuations – becomes more eager to imitate other traders. Furthermore, Chiang and Zheng (2010); Yao et al. (2014) and Litimi et al. (2016) argue that herding behavior becomes more accentuated during turmoil periods. Thus, we revise the model in Eq. (1) by introducing three additional variables: the volume turnover, a dummy variable to highlight major bubbles and financial crises during the studied period, and a sentiment index to highlight the degree of investors insecurity and fear in Eq. (2).

$$\begin{aligned} CSAD_t &= \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 Vol_{m,t} + \gamma_4 Sent_t \\ &\quad + \gamma_5 R^2_{m,t} D_t + \gamma_6 Vol_{m,t} D_t + \gamma_7 Sent_t D_t + \varepsilon_t \end{aligned} \tag{2}$$

Where: $Vol_{m,\, t}$ is the turnover of market trading volume at day t, defined as daily trading volume scaled by daily market capitalization. Lo and Wang (2000) and Statman et al. (2006) propose not to detrend the volume turnover, *i.e.*, by taking the logarithmic difference, to avoid biasing the results against finding a relation between herding behavior and subsequent trades.

The variable *Sent* represents the investors sentiment proxied by the VIX index, often called "*the fear gauge*" because it represents the market's expectation of future volatility over the next 30 days (Baker and Wurgler, 2007).

Herding is noticeably observed during abnormal market conditions; these include both financial crises (downward returns) and bubbles (upward returns). So, the variable D_t takes the value of one during turmoil periods, and null otherwise.

Note that some authors (Chiang and Zheng, 2010) separated the effect of the exogenous variables by multiplying $R^2_{m,t}, Vol_{m,t}, Sent_t$ by $(1-D_t)$ in Eq. (2) to clearly specify their effect during normal periods, besides their effect during turmoil periods. While econometrically this transformation has little effect, we opt for the model employed by Litimi et al. (2016).

The models in Eqs. (1) and (2) are estimated using the Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors to remove any multicollinearity problem if present.

2.3. Herding and market conditional volatility

Market conditional volatility is usually affected by past returns. Any exogenous variable that might affect the market is introduced in the mean equation of the returns. The effect of herding on idiosyncratic volatility has been scantly investigated (Litimi et al., 2016). Indeed, Huang et al. (2015) studied the effect of volatility on herding in the emerging Taiwan equity market; and Majand and Yung (1991) and Venezia et al. (2011) included the transaction volume in the variance equation in the GARCH model to examine the volume-volatility interaction.

If herding is present in the stock market, a group of presumably informed investors trades on a specific stock that they may have privileged information, and leave other stocks without trades; these investors are followed by other imitating traders, which creates abnormally high transaction volume on that specific stock, while neglecting trading on other stocks. Since it takes volume to make prices move (Karpoff, 1987), high trading volume is often followed by high volatility; consequently, the volatility of the concerned stock rises, and if the market is large enough, the overall market average volatility decreases (Litimi et al., 2016). Therefore, herding behavior positively affects a specific stock's volatility, but negatively affects the market average volatility (Hwang and Salmon, 2004). Furthermore, the effect of herding on volatility may differ from sector to sector depending on the group of investors that trades on each industry and the information they perceive. For illustrative purposes, suppose a large market with $X_1, X_2, \dots, X_n$ stocks (n is large); some leading investors trade only on a stock X_i due to some information about the future outcome of the that stock, engendering an increase in the trading volume of X_i. The volatility – proxied by the standard deviation of the returns – of stock X_i raises, while the volatilities of each of the remaining stocks $X_1, X_2, \dots, X_{(i-1)}, X_{(i+1)}, \dots, X_n$ decrease. For large n, the volatility of the average stock returns (all stock including X_i) decreases, because $(n-1)$ volatilities decrease and only one volatility – of stock X_i – increases. The amplitude of the decrease in the overall volatility of the average market returns depends on the proportion between n and the number of active stocks, *i.e.*, if the number of active stocks increases relative to n, the decrease in the overall volatility slows down until it shifts direction and starts to increase (when the proportion exceeds a certain threshold).

The conditional volatility of the average market return is estimated using the asymmetric GJR model of Glosten et al. (1993) in Eq. (3).

$$\begin{cases} R_{m,t} = c + \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \xi_1 I_{[\varepsilon_{t-1}<0]} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{cases} \tag{3}$$

Where c is a proxy for the average market return, and $\varepsilon_t \to IID(0, \sigma_t^2)$ are independently and identically distributed error terms under the Student's t distribution with degrees-of-freedom (*d.f.*) ν. The coefficients α_0, α_1, β_1 are restricted to be positive, and $\alpha_1 + \xi_1 \geq 0$. The leverage effect is captured by the coefficient ξ_1 to add more weight on the conditional volatility for negative shocks $\varepsilon_{t-1} < 0$. We set this model as a benchmark for comparison purposes.

Table 1
Descriptive statistics.

Variable	Market return	Volume turnover	CSAD	Sentiment index
Mean	0.00032889*	0.0013	0.018188	19.824*
Minimum	−0.16877	0.00016	0.008651	9.31
Maximum	0.09847	0.04309	0.14385	80.86
Std. Dev.	0.0095755	0.00142	0.006025	7.92
Skewness	−1.3739	7.6363	3.5325	2.0902
Kurtosis	26.4626	134.888	38.4535	10.588
Jarque-Bera	181,714†	5,740,002†	425,548†	20,493†

* Statistically significant at the 1% significance level.
† The Jarque-Bera test rejects normality for all series.

Next, we add the volume turnover and the CSAD measure into the variance equation to investigate the effect of herding and transaction volume on the market average conditional volatility in Eq. (4).

$$\begin{cases} R_{m,t} = c + \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \xi_1 I_{[\varepsilon_{t-1}<0]} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta Vol_{m,t} + \gamma CSAD_t \end{cases} \tag{4}$$

The coefficients δ and γ are unrestricted to fully capture the dynamics between trading volume, herding and conditional volatility. The peculiarity of GARCH-type models is that the conditional expected value of the squared returns – given the available information on past observations $R_{m,\underline{t-1}}$ up to time $(t - 1)$ – equals the conditional volatility, in other words, $E(R_{m,t}^2 | R_{m,\underline{t-1}}) = \sigma_t^2$. Therefore, if herding is present, the relationship between CSAD and the return squared $R_{m,t}^2$, or its expected value measured by σ_t^2, is negative. Besides, as aforementioned, trading volume negatively affects the market volatility in large markets. Hence, we expect that δ and γ are negative.

3. Data and empirical results

3.1. Data and descriptive statistics

The data correspond to all domestic U.S. firms listed on NYSE/AMEX/NASDAQ, collected from the Center for Research in Security Prices (CRSP). The sample contains 4183 American companies, after removing incomplete data, starting from January 2, 1985 to December 31, 2015; with a total of 7815 daily observations for each firm.[1] Following the NASDAQ classification, the American stock market is divided into 12 sectors.

The sample period encompasses 4 major events: (1) the black Monday on October 19, 1987 (October 1, 1987 – September 29, 1989); (2) the dot-com bubble (January 2, 1997 – March 10, 2000); (3) the stock market downturn of 2002 (September 10, 2001 – October 9, 2002); (4) and finally the global financial crisis (March 3, 2008 – March 31, 2009). The starting and ending dates of each period are exactly the same as in Litimi et al. (2016), and fixed by carefully studying each event.

Table 1 presents the descriptive statistics. Except for the market average return, all other variables take positive values. Technically, the CSAD can only be positive, since it is the sum of absolute values; an exogenous variable that takes both positive and negative values has little or no effect on the strictly positive CSAD; therefore, it makes more sense to include the absolute value of the returns in Eq. (1) rather than the returns themselves. Besides, since the volume turnover and the sentiment index are positive, they can directly influence herding in Eq. (2). The Jarque-Bera test rejects normality for market average return, with a negative skewness being present. Moreover, the leverage effect, per which the volatility is affected more by negative shocks than by positive ones, is usually observed in financial markets (Glosten et al., 1993). This strongly explains the use of the asymmetric GJR-GARCH model under the Student's t distribution in the GARCH estimation.

3.2. CSAD model results

Regression results of Eq. (1) at a sectoral level are presented in Table 2. According to Chang et al. (2000)'s model, herding is absent in all U.S. sectors, since the coefficient γ_2 relative to R_m^2 is either statistically positive, or statistically not different from zero. Therefore, sector returns by themselves are not an incentive for investors to embark into herd behavior; they need more information about the market condition.

3.3. Modified CSAD model

Regression results of the modified Chang et al. (2000)'s CSAD model in Eq. (2) are presented in Table 3. The adjusted $\bar{R}^2$ are significantly improved indicating a good performance of the herding model (Xie et al., 2015), and the coefficient γ_2 becomes positively significant for all sectors. The coefficient γ_3 relative to the volume turnover is negatively significant in

[1] We extend the same sample used in Litimi et al. (2016) until the end of year 2015.

Table 2
Regression of cross sectional absolute deviation on market return.

Sector	*Companies count*	*Constant*	$\lvert R_m \rvert$	R_m^2	$\bar{R}^2$
All	4183	0.014993*(189.9592)	0.51409*(46.0085)	0.0020928(0.011841)	0.387
Basic Industries	189	0.015647*(172.498)	0.38727*(37.4397)	0.51017*(3.5733)	0.346
Capital Goods	314	0.016557*(175.9121)	0.3686*(31.4321)	0.56781*(2.9491)	0.295
Consumer Durables	116	0.015297*(158.0445)	0.29826*(23.1554)	1.9853*(8.5029)	0.258
Consumer Non-Durables	167	0.015863*(172.5855)	0.3936*(35.025)	−0.043301(−0.31963)	0.226
Consumer Services	581	0.014618*(173.6104)	0.44527*(41.23)	0.31235**(1.9627)	0.365
Energy	217	0.017636*(147.5934)	0.16264*(14.744)	5.0027*(51.808)	0.536
Finance	754	0.011539*(155.9709)	0.63778*(52.5967)	0.61836*(2.8813)	0.518
Health Care	473	0.021084*(148.5679)	0.39481*(23.6011)	2.2794*(8.338)	0.237
Miscellaneous	683	0.0082474*(147.1434)	0.64714*(59.5834)	1.1017*(7.4372)	0.582
Public Utilities	181	0.010129*(118.1327)	0.52037*(39.0833)	1.1502*(5.2398)	0.375
Technology	448	0.019479*(146.653)	0.44222*(33.4299)	0.53708*(2.6813)	0.304
Transportation	60	0.013471*(103.339)	0.4588*(34.4797)	−0.050238(−0.27275)	0.269

Note: this table reports the regression results of the model of Chang et al., (2000) in Eq. (1). Numbers in parentheses are *t*-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors. All γ_2 coefficients are either statistically positive or not different from zero indicating the absence of herding.

*, ** Significant at the 1% and 5% significance level, respectively.

only 2 sectors out of 12 (Health care and Public utilities), besides the whole market. Indeed, as argued by BenSaïda et al. (2015), trading volume could be a potential reason for investors to herd around the market. Since trading volume is a good indication of market liquidity, *i.e.*, active trading is not possible when the market lacks cash to complete the transactions; on the contrary, investors can earn quick returns for highly liquid stocks because multiple transactions yield rapid income (positive or negative) when the market provides fast cash.

The dummy variable D_t takes the value of one during the following 4 events (and null otherwise): (1) the black Monday from October 1, 1987 till September 29, 1989; (2) the dot-com bubble from January 2, 1997 till March 10, 2000; (3) the stock market downturn from September 10, 2001 till October 9, 2002; (4) and finally the global financial crisis from March 3, 2008 till March 31, 2009.

The inclusion of D_t enhances the detection of herding during financial turmoil periods. In fact, the coefficient γ_5 relative to $R_m^2 \times D$ becomes significantly negative for the whole market and for 10 sectors out of 12, and negative for the remaining 2 sectors. We conclude that during financial crises and bubbles, the investors panic and sideline their own private information, choosing to blindly copy presumably well informed traders, thus entering into a herding movement.

The volume turnover during financial turmoil periods does not enhance herding in any sector, since all γ_6 coefficients are significantly positive. Moreover, the introduction of investors' sentiment enhances herding during turmoil periods in only 4 sectors (significantly negative values are observed for γ_7 relative to $Sent \times D$ for Basic industries, Consumer durables, Finance, and Public utilities).

3.4. GARCH estimation

For comparison purposes, the estimates from Eq. (3) are presented in Table 4. All coefficients are highly significant at the 1% significance level indicating the validity of the GJR model. Furthermore, the Student's *t* degrees-of-freedoms (*d.f.*) are larger than 2, which confirms the non-normality of the data. Model selection is based on the Schwarz information criteria (SIC) reported in the last column. Leverage coefficients ξ_1 are positively significant for all sectors indicating that future expected volatility tends to be higher when actual returns are negative than when they are positive.

Results of the modified GJR model of Eq. (4) are presented in Table 5. According to the SIC, the model has been substantially improved for the entire U.S. stock market, and for 6 sectors out of 12 (Energy, Health care, Miscellaneous, Public utilities, Technology, and Transportation).

We notice that herding negatively affects the conditional volatility of the average sector returns in 10 sectors, excluding Capital goods and Consumer durables, where, although the γ coefficients relative to CSAD are negative, they are still insignificant. For the volume turnover, it negatively affects the volatility in 5 sectors besides the whole market; this contradicts the rational stylized fact discussed by Cont (2001), where he stated that trading volume is positively correlated with all measures of volatility. Indeed, Blasco et al. (2012) argue that, in the presence of herd behavior, the volatility decreases as the average trading volume increases, because informed investors engage in higher trading, and the larger the trade size, the higher the informed trading; therefore, the less volatility in the market. Thus, when herding is present, heavy trading negatively affects the market return volatility.

For the Miscellaneous sector, the coefficient δ relative to Vol_m is statistically positive. We deduce that informed investors in that sector are fewer than in other sectors, or the investors do not recognize informed from uninformed traders (Litimi et al., 2016). Consequently, they cannot influence the market to embark into a herding behavior, since heavy trading on specific stocks in the Miscellaneous sector is barely noticeable.

Table 3
Results of the modified herding model.

Sector	*Constant*	$\lvert R_m \rvert$	R_m^2	Vol_m	*Sent*	$R_m^2 \times D$	$Vol_m \times D$	$Sent \times D$	$\bar{R}^2$
All	0.011353*(69.6097)	0.20836*(14.4948)	4.0188*(8.3909)	−0.1585*(−3.3022)	0.00028*(30.7347)	−2.8541*(−7.2095)	2.3605*(10.811)	3.6305e-05*(4.2964)	0.591
Basic Industries	0.011944*(66.0693)	0.20466*(16.2943)	0.649***(1.9532)	0.51611*(6.9159)	0.000257*(26.0036)	−0.40892(−1.5144)	9.1104*(17.4584)	−8.6e-05*(−7.5252)	0.521
Capital Goods	0.011561*(62.328)	0.15492*(11.4681)	0.8731**(2.3007)	1.1214*(9.3469)	0.000316*(30.4495)	−0.52***(−1.6919)	4.983*(12.2513)	−1.5873e-05(−1.4562)	0.519
Consumer Durables	0.011358*(60.3827)	0.11246*(7.6281)	2.0522*(4.7481)	0.031482(0.67613)	0.000285*(27.1635)	−0.48369(−1.3717)	5.6091*(12.7693)	−2.47e-05**(−2.0852)	0.468
Consumer Non-Durables	0.013318*(69.4585)	0.09842*(5.7487)	5.5254*(10.2449)	−0.00043(−0.0922)	0.000197*(18.3453)	−3.4036*(−7.4372)	0.146**(2.2236)	0.00015*(19.088)	0.426
Consumer Services	0.01062*(59.9988)	0.16232*(11.4099)	3.5392*(8.0645)	0.06396*(4.0552)	0.000283*(28.4157)	−1.8808*(−5.2366)	0.52539*(10.733)	5.6905e-05*(8.4237)	0.559
Energy	0.014185*(56.2397)	0.10294*(9.1485)	6.747*(74.9869)	1.0747*(13.0046)	0.000142*(10.4701)	−5.7535*(−40.437)	6.2371*(12.6082)	5.6906e-05*(4.0023)	0.691
Finance	0.006392*(45.6933)	0.31706*(23.8977)	4.9847*(11.913)	3.7906*(27.8163)	0.000271*(33.5818)	−2.1599*(−6.1583)	10.7293*(16.4362)	−3.81e-05*(−4.5666)	0.721
Health Care	0.019625*(79.2869)	0.06569*(3.9179)	10.025*(28.7088)	−0.599*(−11.68)	0.000236*(17.7403)	−6.9657*(−18.193)	1.7763*(7.7618)	0.0001615*(15.3653)	0.499
Miscellaneous	0.005081*(50.9746)	0.38877*(42.1768)	5.2117*(30.9843)	0.3013*(11.6258)	0.000182*(32.1831)	−5.4604*(−32.517)	1.8964*(6.6086)	−4.2131e-07(−0.059298)	0.712
Public Utilities	0.007872*(45.2755)	0.13197*(9.3827)	12.7929*(38.7803)	−1.6533*(−8.3377)	0.00024*(24.9246)	−11.919*(−37.9)	10.9585*(17.0241)	−3.51e-05*(−3.3349)	0.596
Technology	0.015465*(56.8693)	0.25087*(15.5235)	3.3002*(10.1869)	0.49284*(8.7406)	0.000215*(14.4942)	−4.5755*(−13.683)	4.0397*(8.7508)	8.475e-05*(4.1314)	0.451
Transportation	0.012676*(45.7589)	0.06582*(3.6377)	9.7139*(22.9462)	0.8738*(7.5579)	0.000124*(8.4141)	−7.4296*(−21.02)	3.2771*(7.3993)	9.242e-05*(6.2039)	0.389

Note: this table reports the regression results of the modified CSAD model in Eq. (2). Numbers in parentheses are *t*-statistics based on Newey-West (1987)'s heteroskedasticity and autocorrelation consistent standard errors. The significant negativity of γ_3 indicates that the volume turnover seems to fuel herding for the entire market along with 2 sectors, independently whether the market is during turmoil periods or not. Furthermore, the significant negativity of γ_5 indicates that the sector returns trigger herding during financial bubbles and crises in 10 sectors.

*, **, *** Significant at the 1%, 5%, and 10% significance level, respectively.

Table 4
GJR-GARCH estimation.

Sector	*Offset*	α_0	$\varepsilon^2_{m,t-1}$	*Leverage*	σ^2_{t-1}	*d.f.*	SIC
All	0.000899*(13.2364)	1.13e-06*(7.4543)	0.050768*(5.1704)	0.095818*(8.3202)	0.88164*(109.1097)	6.1695*(16.4238)	−55,126.75
Basic Industries	0.000724*(8.2712)	8.78e-07*(5.7441)	0.044474*(6.1405)	0.05001*(6.003)	0.9222*(164.2406)	7.0308*(15.553)	−51,006.07
Capital Goods	0.000837*(9.651)	1.24e-06*(6.3239)	0.054299*(6.1681)	0.058558*(6.1437)	0.9033*(127.0242)	7.3279*(14.7529)	−51,463.53
Consumer Durables	0.000657*(7.5526)	1.40e-06*(6.8505)	0.034528*(4.7117)	0.072512*(8.0995)	0.91164*(132.8484)	8.3877*(13.2491)	−51,942.28
Consumer Non-Durables	0.000776*(9.5568)	1.68e-06*(7.3294)	0.034282*(4.3798)	0.070913*(7.5185)	0.90493*(115.3349)	7.0817*(16.8434)	−53,133.06
Consumer Services	0.000795*(10.1526)	1.37e-06*(7.2269)	0.044013*(5.1771)	0.083837*(8.2785)	0.8945*(115.0127)	7.1859*(15.5689)	−53,240.80
Energy	0.000740*(7.3991)	1.19e-06*(6.0174)	0.035902*(5.8001)	0.054628*(7.039)	0.92765*(172.3103)	7.0661*(19.6701)	−48,886.71
Finance	0.000784*(12.8946)	8.49e-07*(7.0995)	0.057396*(6.4291)	0.067477*(6.5069)	0.89088*(114.2925)	7.0121*(17.0248)	−56,968.94
Health Care	0.000818*(8.184)	3.33e-06*(7.648)	0.064498*(6.6742)	0.061199*(5.7014)	0.87544*(94.7845)	6.6854*(17.4753)	−49,890.12
Miscellaneous	0.000698*(16.3995)	8.35e-07*(9.1622)	0.065034*(6.723)	0.12959*(9.4363)	0.84453*(91.6947)	4.808*(22.7622)	−61,779.57
Public Utilities	0.000732*(11.5786)	1.01e-06*(7.4054)	0.058551*(6.1905)	0.075778*(6.3254)	0.88641*(117.7277)	5.9898*(18.9661)	−56,095.08
Technology	0.000776*(6.3301)	3.39e-06*(7.2171)	0.043614*(5.5459)	0.077983*(8.2909)	0.8946*(108.9376)	10.3084*(10.8261)	−46,976.07
Transportation	0.000567*(5.0288)	2.96e-06*(6.6835)	0.034951*(4.675)	0.055939*(5.8896)	0.91551*(122.6219)	6.8501*(17.7886)	−47,980.91

Note: this table reports the estimation results of the GJR model presented in Eq. (3). Numbers in parentheses are *t*-statistics. All coefficients are highly significant.

* Significant at the 1% significance level.

Table 5
Modified GJR-GARCH estimation.

Sector	*Offset*	α_0	$\varepsilon^2_{m,t-1}$	*Leverage*	σ^2_{t-1}	$Vol_{m,\ t}$	$CSAD_t$	*d.f.*	SIC
All	0.00089254* (13.0292)	2e-07(0.36438)	0.048354*(4.574)	0.11504*(9.0014)	0.86462*(92.7953)	−0.00035514*(−2.8519)	−5.7586e-05***(−1.9298)	6.3295*(15.5949)	−55,129.50
Basic Industries	0.00071395*(8.0776)	2e-07(0.34741)	0.044457*(5.5849)	0.060117*(6.527)	0.91133*(139.0538)	−5.8927e-05**(−2.4197)	−5.7166e-05***(−1.6681)	7.2019*(15.0014)	−51,003.41
Capital Goods	0.00083494*(9.5837)	2e-07(0.29594)	0.054465*(5.8927)	0.0661*(6.524)	0.89617*(117.0212)	−0.00057661(−1.614)	−4.777e-05(−1.5583)	7.3781*(14.5194)	−51,451.84
Consumer Durables	0.00065248*(7.4928)	8.4762e-07(1.5943)	0.03543*(4.6931)	0.073759*(8.0171)	0.90892*(127.952)	−0.00013374(−0.55504)	−3.2938e-05(−1.2514)	8.4274*(13.1694)	−51,925.28
Consumer Non-Durables	0.00077358*(9.5193)	6.4806e-07(1.1946)	0.032588*(3.9345)	0.082569*(7.9546)	0.89209*(100.6313)	−0.00020272*(−3.0347)	−6.6558e-05**(−2.2624)	7.1911*(16.4986)	−53,126.06
Consumer Services	0.00079526*(10.134)	2e-07(0.3635)	0.045721*(4.9767)	0.093914*(8.4128)	0.88067*(99.6904)	−0.000242**(−2.165)	−7.6898e-05**(−2.3298)	7.3703*(14.538)	−53,231.96
Energy	0.00073172*(7.1701)	2e-07(0.25768)	0.039072*(5.3764)	0.065358*(7.2505)	0.91018*(133.1125)	−0.00078686***(−1.9207)	−7.3063e-05***(−1.9433)	7.3313*(16.3507)	−48,892.50
Finance	0.00077084*(12.5114)	2e-07(0.56497)	0.059994*(5.8297)	0.089588*(7.0991)	0.86556*(90.992)	−0.00026538(−1.3904)	−7.2832e-05*(−2.7991)	7.2388*(15.8272)	−56,968.53
Health Care	0.00079902*(7.8376)	2e-07(0.14117)	0.055113*(4.7513)	0.10539*(7.4601)	0.81908*(59.6781)	−0.0018987*(−4.2168)	−0.00021786*(−3.7419)	7.1392*(15.0652)	−49,938.47
Miscellaneous	0.00067195*(15.0147)	2e-07(0.37672)	0.094776*(6.0907)	0.23164*(9.5298)	0.67782*(39.2538)	6.7981e-05*(6.7071)	−0.00029026*(−5.3114)	5.1543*(16.9842)	−61,854.13
Public Utilities	0.00070721*(10.8149)	2e-07(0.32236)	0.058004*(4.9284)	0.11482*(7.39)	0.82998*(71.9893)	−0.00041784(−1.3061)	−0.00018962*(−3.4875)	6.275*(16.2504)	−56,138.26
Technology	0.00072436*(5.8466)	2e-07(0.17766)	0.034682*(3.8204)	0.10947*(9.409)	0.8625*(78.3112)	0.00012338(0.74683)	−0.00030677*(−4.7969)	11.2077*(9.6194)	−47,008.59
Transportation	0.00039385*(3.2931)	2e-07(0.028686)	0.061218*(3.5203)	0.088272*(3.3538)	0(0)	0.00075662(0.24126)	−0.0071538*(−18.0439)	7.037*(12.1605)	−48,079.45

Note: this table reports the regression results of the modified GJR model in Eq. (4). Numbers in parentheses are t-statistics. Negative γ coefficient indicates that herding inhibits the conditional volatility of the average sector return. And negative δ coefficient indicates that the volume turnover reduces the overall volatility.

*, **, *** Significant at the 1%, 5%, and 10% significance level, respectively.

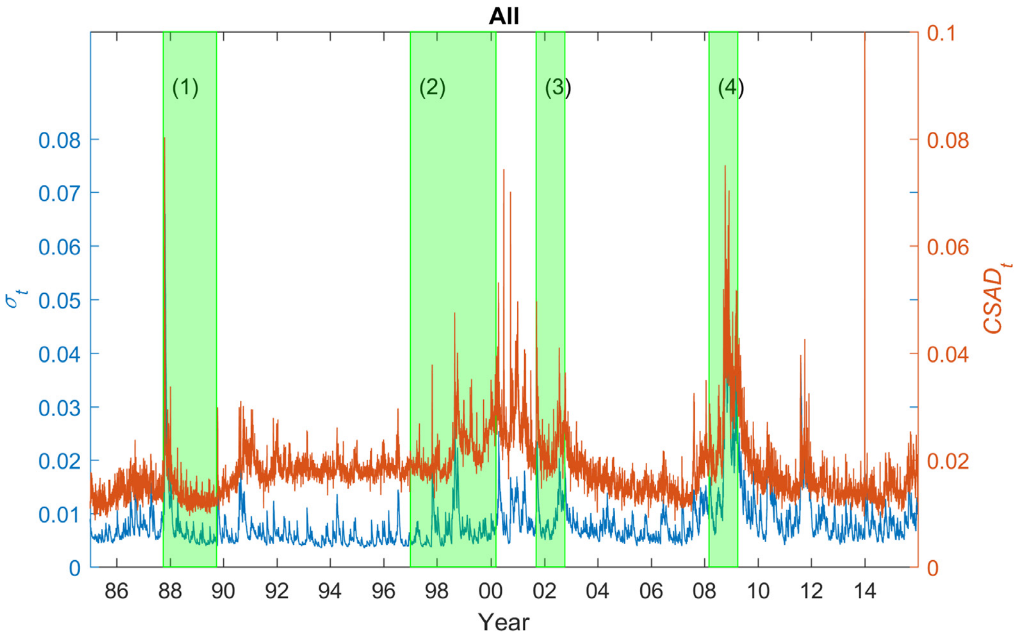

Fig. 1. Conditional volatility *vs*. CSAD for the entire U.S. market.

Moreover, as argued by Holmes et al. (2013), when the volatility is low, herding is expected to be more pronounced. Therefore, a negative relationship between herding and the conditional volatility constitutes evidence of the presence of herd behavior (Litimi et al., 2016).

The average return market conditional volatility is compared to the CSAD measure for the entire U.S. market in Fig. 1. Additionally, Fig. 2 plots the conditional volatility for all sectors compared to their respective CSAD. The shaded areas represent the four turmoil periods: (1) the black Monday, (2) the dot-com bubble, (3) the stock market downturn, (4) and finally the global financial crisis. We deliberately choose the same axes for comparison purposes.

The cross sectional absolute deviation (CSAD) is larger than the conditional volatility in all sectors. During financial turmoil, the CSAD becomes larger than other periods, and so does the volatility, yet with lower amplitude. Although graphical representation shows that both the CSAD and the conditional volatility in every sector become larger during crises and bubbles, the amplitude of the volatility is mitigated by investors' herding (Table 5).

4. Conclusion

Herding is present in the U.S. stock market only during financial crises and bubbles starting from the black Monday of 1987 until the last global financial crisis. The original CSAD model does not provide sufficient evidence of the presence of herding; however, the modified CSAD model indicates that investors herd around the market in 10 out of 12 sectors. Furthermore, the volume turnover does not seem to trigger herding, whether during turmoil or tranquil periods. However, the investors' sentiment actively contributes to the intensity of herding in only 4 sectors. Indeed, during financial crises and bubbles, the investors panic and sideline their own private information, choosing to blindly copy presumably well informed traders, thus entering into a herding movement.

Our empirical investigation provides an explanation to the association between herding and market conditional volatility. Actually, herding affects a relatively small number of specific stocks' volatility. Consequently, the overall market volatility decreases due to the decrease of the inactive remaining stocks not affected by herding behavior. Thus, herding has an inhibiting effect on the average returns' volatility for all sectors.

Moreover, trading volume inhibits the conditional volatility for the entire market, and for some sectors; since informed investors engage in higher trading than uninformed ones, and the larger the observed trade size, the higher the amount of informed trading; therefore, the less volatility in the market. Nevertheless, trading volume positively affects the conditional volatility in the Miscellaneous sector; we suspect that informed traders are relatively fewer in this sector, or the investors cannot separate informed from uninformed traders; so, higher trading on specific stocks is less noticeable, and the volatility of the average sector return becomes positively affected by the volume turnover.

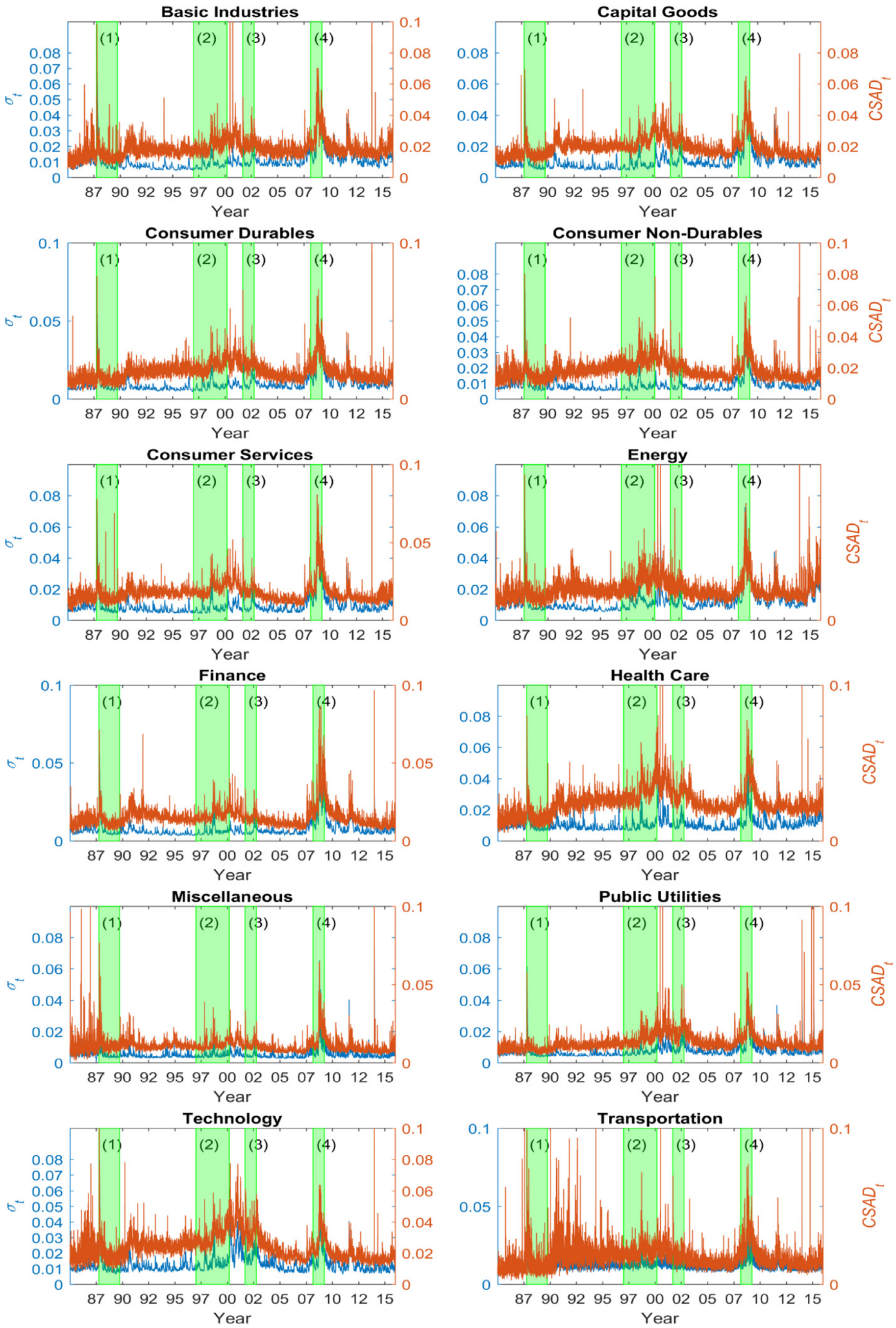

Fig. 2. Conditional volatility *vs*. CSAD per sector.

References

Babalos, V., Balcilar, M., Gupta, R., 2015. Herding behavior in real estate markets: novel evidence from a Markov-switching model. J. Behav. Exp. Finance 8, 40–43.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21 (2), 129–152.

Balcilar, M., Demirer, R., Hammoudeh, S., 2014. What drives herding in oil-rich, developing stock markets? Relative roles of own volatility and global factors. North Am. J. Econ. Finance 29, 418–440.

Ben Mabrouk, H., Fakhfekh, M., 2013. Herding during market upturns and downturns: international evidence. IUP J. Appl. Finance 19 (2), 5–26.

BenSaïda, A., Jlassi, M., Litimi, H., 2015. Volume - herding interaction in the American market. Am. J. Finance Account. 4 (1), 50–69.

Blasco, N., Corredor, P., Ferreruela, S., 2012. Does herding affect volatility? Implications for the Spanish stock market. Quant. Finance 12 (2), 311–327.

Boubaker, S., Farag, H., Khuong Nguyen, D., 2015. Short-term overreaction to specific events: evidence from an emerging market. Res. Int. Bus. Finance 35, 153–165.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: an international perspective. J. Bank. Finance 24 (10), 1651–1679.
Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. Finance 34 (8), 1911–1921.
Choi, N., Sias, R.W., 2009. Institutional industry herding. J. Financ. Econ. 94, 469–491.
Christie, W.G., Huang, R.D., 1995. Following the pied piper: do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37.
Chuang, W.I., Lee, B.S., 2006. An empirical evaluation of the overconfidence hypothesis. J. Bank. Finance 30 (9), 2489–2515.
Cont, R., 2001. Empirical properties of asset returns: stylized facts and statistical issues. Quant. Finance 1 (2), 223–236.
Dehghani, P., Sapian, R.Z.Z., 2014. Sectoral herding behavior in the aftermarket of Malaysian IPOs. Venture Cap. 16 (3), 227–246.
Demirer, R., Kutan, A.M., Chen, C.-D., 2010. Do investors herd in emerging stock markets?: evidence from the Taiwanese market. J. Econ. Behav. Organ. 76 (2), 283–295.
Dennis, P.J., Strickland, D., 2002. Who blinks in volatile markets, individuals or institutions? J. Finance 57 (5), 1923–1949.
Economou, F., Kostakis, A., Philippas, N., 2011. Cross-country effects in herding behaviour: evidence from four south European markets. J. Int. Financ. Markets Inst. Money 21 (3), 443–460.
Evans, J., Borders, A.L., 2014. Strategically surviving bankruptcy during a global financial crisis: the importance of understanding chapter 15. J. Bus. Res. 67 (1), 2738–2742.
Gabaix, X., Gopikrishnan, P., Plerou, V., Stanley, E.H., 2006. Institutional investors and stock market volatility. Q. J. Econ. 121 (2), 461–504.
Gebka, B., Wohar, M.E., 2013. International herding: does it differ across sectors? J. Int. Financ. Markets Inst. Money 23, 55–84.
Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. The J. Finance 48 (5), 1779–1801.
Hausman, A., Johnston, W.J., 2014. Timeline of a financial crisis: introduction to the special issue. J. Bus. Res. 67 (1), 2667–2670.
Henker, J., Henker, T., Mitsios, A., 2006. Do investors herd intraday in Australian equities? Int. J. Managerial Finance 2 (3), 196–219.
Holmes, P., Kallinterakis, V., Ferreira, M.P., 2013. Herding in a concentrated market: a question of intent. Eur. Financ. Management 19 (3), 497–520.
Huang, T.C., Lin, B.H., Yang, T.H., 2015. Herd behavior and idiosyncratic volatility. J. Bus. Res. 68 (4), 763–770.
Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Finance 11 (4), 585–616.
Karpoff, J.M., 1987. The relation between price changes and trading volume: a survey. J. Financ. Quant. Anal. 22 (1), 109–126.
Kremer, S., Nautz, D., 2013. Causes and consequences of short-term institutional herding. J. Bank. Finance 37 (5), 1676–1686.
Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. J. Financ. Econ. 32 (1), 23–43.
Litimi, H., BenSaïda, A., Bouraoui, O., 2016. Herding and excessive risk in the American stock market: a sectoral analysis. Res. Int. Bus. Finance 38, 6–21.
Lo, A.W., Wang, J., 2000. Trading volume: definitions, data analysis, and implications of portfolio theory. Rev. Financ. Stud. 13 (2), 257–300.
Lux, T., 1995. Herd behaviour, bubbles and crashes. Econ. J. 105 (431), 881–896.
Majand, M., Yung, K., 1991. A garch examination of the relationship between volume and price variability in futures markets. J. Futures Markets 11 (5), 613–621.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. 28 (3), 777–787.
Nofsinger, J.R., Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. J. Finance 54 (6), 2263–2295.
Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19 (4), 1531–1565.
Tan, L., Chiang, T.C., Mason, J.R., Nelling, E., 2008. Herding behavior in Chinese stock markets: an examination of A and B shares. Pacific-Basin Finance J. 16 (1-2), 61–77.
Venezia, I., Nashikkar, A., Shapira, Z., 2011. Firm specific and macro herding by professional and amateur investors and their effects on market volatility. J. Bank. Finance 35 (7), 1599–1609.
Xie, T., Xu, Y., Zhang, X., 2015. A new method of measuring herding in stock market and its empirical results in Chinese A-share market. Int. Rev. Econ. Finance 37, 324–339.
Yao, J., Ma, C., He, W.P., 2014. Investor herding behaviour of Chinese stock market. Int. Rev. Econ. Finance 29 (1), 12–29.