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# Herd behavior and idiosyncratic volatility in a frontier market

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ABSTRACT

This study investigates the impact of idiosyncratic volatility on the herd behavior of individual investors in Vietnam stock market covering the period from 2005 to 2016. We employ the herding methods of Christie and Huang (1995) and Chang et al. (2000) and single factor model by Bali and Cakici (2008) to estimate the idiosyncratic volatility. Empirical results indicate that herding exists in this equity market. However, herding behavior displays distinct patterns under different stock portfolios depending on the levels of idiosyncratic volatility. The results are robust under various timeframes including pre-crisis, during crisis and post-crisis. The finding also reveals the existence of herding under particular industry.

## 1. Introduction

Understanding the dynamic movement of financial market is one of interesting challenges to researchers. Notwithstanding much effort in analyzing the stock price movement, the financial market is still enigmatic and nearly defies all of standard financial theories, particularly in the extreme volatile events. After the aftermath of the global financial crisis, the traditional asset pricing theory in which the Capital Asset Pricing Model (CAPM) is the most well-known and basic model fail to explain the volatility of excess return in financial market. Recently, behavioral finance has developed a more realistic and reasonable explanation to the clustered market volatility, which build on the social and psychological rules. The behavioral perspective assumes that the reaction of human to the event generates the fluctuation rather than the event themselves (Litimi et al., 2016). In other words, the market volatility is derived from the volatile emotion and belief of the investors (Bensaida, 2017), which engages in herd behavior. Herd behavior itself constitutes an evidence to oppose the rational theory (Lao and Singh, 2011).

Herding or herd behavior corresponds to the action of investors who ignore their own private information to follow the collective behavior, even if this action is not supported by fundamental information (Litimi et al., 2016). In this case, investors will imitate the investment strategies of other peers, either because they do not have information or they believe that other market participants possessive more accurate and reliable sources of information. If this phenomenon lasts longer and the market fails to adjust the stock price towards its intrinsic value, herding consequently generates the stock volatility and leads to the market destabilization (Vo and Phan, 2017). Further, herding is more prominent for smaller equity markets (Arjoon and Bhatnagar, 2017).

Herding affects stock market stability because herding is associated with a decrease in heterogeneity among investors (Nianhang et al., 2017; Schmitt and Westerhoff, 2017). Total volatility of individual stocks can be decomposed into two categories including systematic volatility which is non-diversifiable and idiosyncratic volatility which represents the uncertainty of a single firm. As

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idiosyncratic volatility can be eliminated by diversification in portfolios, traditional asset pricing models ignore the effect of it and make a concentration only on the market risk. However, in some cases of the wealth constraints or by any reasons of favorite choices (Malkiel and Xu, 2003), many individual investors do not hold diversified portfolios; instead, they require higher return for bearing the idiosyncratic risk of their stocks (Merton, 1987). Hence, investors still gain their care about the specific risk of the securities they hold; in other words, idiosyncratic volatility still need further investigation in academic research.

The institutional characteristics of Vietnam stock market in which the Ho Chi Minh City stock exchange plays a key role are our first strong motivation for this paper. While Vietnamese government has been improved legal institutional framework and reinforced investment environment, information transparency has been a remained issue with negative impacts causing the impediment of investment flow from outside investors into the local market. It is undeniable that there has been existing a series of violation relating to information transparency in Vietnam stock market from its establishment until now. One of the most important consequence is that the non-transparency is the primary factor leading to herd behavior. Furthermore, with the constant development and higher attractiveness of such market, Vietnam stock market has gained more attention from domestic and foreign investors to invest in. Up till now, foreign investors have legal right to hold more than 50% of shares in local firms. Thus, the presence of herding propensity can result in numerous negative consequences and the stock market will become deteriorating. Therefore, it is essential to have a further investigation to deeply analyze this trading behavior in Vietnam stock market. Moreover, this paper examines the propensity in both aggregate market level, sectoral level and even specific firm perspective through the analysis of herding within different sectors and the link between herding and idiosyncratic volatility.

Our second motivation is derived from the lack of articles taking into account the herd behavior under firm-specific perspective. There have been fast-growing studies on idiosyncratic volatility in the current literature. Most of previous studies have focused on examining the issue with assumptions that people are rational and nearly overlooked the importance of investors' behavior. Nevertheless, Huang et al. (2015) argued that when undiversified investors imitate the decision making strategies of other market participants, the idiosyncratic volatility might substantially affect herd behavior. A few previous papers paid less attention to this issue (Dennis and Strickland, 2009; Fernandez, 2014). Therefore, a better understanding of the linkage between herding and idiosyncratic volatility is crucial.

Besides, we also focus our analysis of herding on industry levels for a number of points. The first motivation arises from the importance of industry allocation. Hou (2007) suggests that information diffusion is more prevalent for firms in the same industry because these firms move closely with each other regarding the products and technology innovations. Investors enable to extrapolate information about a given firms based on information about other firms in the same industry; thus, make trade decision based on sectoral analysis (Choi and Sias, 2009). Moreover, Demirer et al. (2010) assert that financial analysts and money managers who herd for reputation and compensation tend to signal information from their industrial classifications and make recommendations at a sector level. Secondly, most of current herding industrial analyses cover developed equity markets (Choi and Sias, 2009; Christie and Huang, 1995) while previous research concerning this issue in the context of emerging stock markets remains light. Besides, there is modicum of literature examining herding in Vietnam stock market at industry level. To the best of our knowledge, this paper will be the first to investigate herding in industry context under various market conditions and different sub-periods in Vietnam equity market.

Our paper highlights the impact of idiosyncratic volatility on investment behavior of market participants. More specifically, we examine the existence of herding and its asymmetric effect under various market conditions within different levels of idiosyncratic volatility. This paper also shed further light on the presence of herding and its degrees under up and down markets within different industries. In addition, we divide the sample into three sub-periods including periods of before financial crisis (BFC), during crisis (FC) and after financial crisis (AFC) to analyze the impact of global financial meltdown on traders' investment strategies. The whole sample consists of 334 firms listed on the Ho Chi Minh City stock exchange covering the period from 2005 to 2016. We employ two influential herding measures to investigate this phenomenon in this study. They are the cross-sectional standard deviation (CSSD) proposed by Christie and Huang (1995) and cross-sectional absolute deviation (CSAD) developed by Chang et al. (2000).

Our study differs from previous papers in several fronts and thus contributing to the existing literature in some important ways. Firstly, this paper is among the first to investigate the trading behavior engaging in herding not only in aggregate market level but also in sectoral analysis and even firm-specific perspectives. Besides, to the best of our knowledge, we are the first to investigate herding asymmetry under up and down-market conditions in different periods based on three groups according to the levels of idiosyncratic volatility in the context of a key emerging market. This study helps to analyze deeper the relation between specific risk of a single firm and investors' behavior; hence, implies some implications for market participants in forming investment strategies. Secondly, we investigate herding across industries. We focus on three main sectors including financial industry, banking sector; and especially, technology sector which gains more attention from academic researchers and investors during the upcoming 4.0 industrial revolution. To the extent of our knowledge, we are the first to examine different classifications under various market conditions and timeframe, especially financial crisis in 2008 in the context of Vietnam stock market. Furthermore, a majority of studies investigate the industrial herding by specific investors, for example institutional investors (Choi and Sias, 2009), fund managers (Hong and Yi, 2006), and retail investors (Jame and Tong, 2009). Therefore, our paper contributes to analyzing the herding by sectors for the aggregate market to measure the shift of investing style in the overall economy rather than only in specific types of investors.

This remainder of the paper has the following structure. Section 2 summarizes a review of literature on herd behavior relating to the conditional volatility. Section 3 describes data and methodology used in this paper. Section 4 reports the empirical results regarding the presence of herding under various levels of idiosyncratic volatility and different industrial groups and Section 5 concludes the paper.

## 2. Literature review

Herd behavior has gained the prevalence in financial literature, particularly in the aftermath of numerous widespread global crises. Theoretically, several authors claim that herd behavior aggravates market volatility and even leads to the instability (Bikhchandani and Sharma, 2001; Guney et al., 2017; Scharfstein and Stein, 1990; Spyrou, 2013). On the empirical side, many previous papers investigate the presence of herding in both advanced and emerging stock markets, which is synthesized in (Vo and Phan, 2016, 2017). They focus on the examination of herd behavior under different market conditions and the impact of global financial crisis on this phenomenon.

A variety of work investigates the relationship between stock return and volatility but a small number of studies provide a direct impact of idiosyncratic volatility on herding. Chang and Dong (2006) investigate the relationship between institutional herding and firms' idiosyncratic volatility using Japanese data during the period from 1975 to 2003. The results show a positive relation with strong evidence that firms in which institutional herding occurs have high idiosyncratic volatility. This finding is consistent with the findings concluded by Tan and Henker (2010). They investigate the monthly idiosyncratic volatility and the proportion of retail trading in Australian stock market during the period 1996–2002. Their monthly return analysis reveals that retail investors have a preference for stocks with high idiosyncratic volatility. Recently, Huang et al. (2015) examine the impact of idiosyncratic volatility on herding in Taiwan equity market covering the period from 2004 to 2013. Empirical results indicate that herding exists in this stock market and varies with the level of idiosyncratic volatility. More specifically, the findings report no herding existence found in stocks with smaller idiosyncratic volatility while it is evidenced in stock portfolios with larger idiosyncratic volatility. The authors also reveal that financial crisis enhances herding, particularly portfolios with the highest idiosyncratic volatility. Moreover, the results show no asymmetric response to news over market stress period with different levels of idiosyncratic volatility.

Although Lee et al. (2013) point out the importance of sectoral indexes as a benchmark to assess the performance of actively managed portfolios, studies on herding are widely applied to the market level, only few of researcher focus on industrial herding (Choi and Sias, 2009; Christie and Huang, 1995). Henker et al. (2006) conclude that herding is more pronounced in materials, consumer staples and financial industries in Australian stock market while Gebka and Wohar (2013) find that sectors such as basic materials, consumer services, and oil and gas reveal herding more than any other sectors. These author claim that herding is not detected when focusing on the world-wide level but when deeper analyzing by examining different economic industries separately, herding displays in some sectors. Litimi et al. (2016) modify the herding model in spirit of Chang et al. (2000) by including trading volume and investor sentiment, they find the presence of herd behavior in 6 out of 12 sectors in American stock market (consumer non-durables, energy, health care, public utilities, technology and transportation); moreover, the stock return by industry generates herding during financial crisis. However, with the same context, Bensaida (2017) indicates that investors herd around the market in 10 out of 12 sectors in the US.

## 3. Methodology

### 3.1. Data collection

The data are collected from 334 firms listed on the Ho Chi Minh City stock exchange (HSX) over the period from January 4, 2005 to July 29, 2016. Our data consist of individual stocks and the VN-Index as the proxy for market returns with the number of daily observations is 2883 in total.

To measure the impact of financial crisis on herding, we perform three sub-periods analysis with the definition of financial crisis period in accordance with Beltratti and Stulz (2012). This paper defines three periods as follows: (1) The period before financial crisis (BFC) is from January 4, 2005 to June 30, 2007, with 620 daily observations; (2) The period of financial crisis (FC) comprises July 1, 2007 to December 31, 2008, with 377 trading days; and (3) the period after the crisis (AFC) covers from January 1, 2009 to July29, 2016, with the number of observations is 1886.

To investigate whether idiosyncratic volatility affects herding, we divide the sample into three groups according to the level of idiosyncratic volatility of each stock. Group 1 consists of stocks with the smallest idiosyncratic volatility, while group 3 comprises stocks with the largest idiosyncratic volatility. Estimations in detail are presented in the next section. For the examination of herding across industries, we separate the sample into four main categories including financial sectors with 11 firms, banking sectors with 6 firms, technology sectors with 3 firms, and the other industries group consists of the remaining stocks.

### 3.2. The idiosyncratic volatility

We employ a single factor model (Bali and Cakici, 2008) to estimate idiosyncratic volatility as follows:

$$R_{i,t} = \alpha + \beta_1 R_{m,t} + \varepsilon_{i,t} \tag{1}$$

$$Idiovolati_{i,t} = (Var(\varepsilon_{i,t}))^{1/2} \tag{2}$$

Where $R_i$ and $R_m$ are return of individual stock i and market, respectively. $\varepsilon_i$ is regression residuals. $Idiovolati_i$ denotes idiosyncratic volatility of individual stock i which is the standard residuals deviation.

### 3.3. The cross-sectional standard deviation method (CSSD) and the cross-sectional absolute deviation of returns method (CSAD)

As herding exists in stock market, individual returns tend to cluster around market returns leading to the decrease of return dispersion from market return. Similarly to the CSSD method proposed by Christie and Huang (1995), the return dispersion is measured as the following specification:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2}{(N-1)}} \tag{3}$$

where $R_{i,\,t}$ is the observed stock return of firm i at time t and $R_{m,\,t}$ is the cross-sectional average of N stock returns in the portfolio at time t.

Christie and Huang (1995) argue that herding is more prevalent in large price swings. Therefore, they examine the presence of herding in different extreme market conditions as follows:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{4}$$

Where $D_t^L = 1$, if the return on the market for time period t lies in the extreme lower tail of the returns distribution, and zero otherwise.$D_t^U = 1$, if the return on the market for time period t lies in the extreme upper tail of the returns distribution, and zero otherwise.

When herding occurs, $\boldsymbol{CSSD_t}$ will be smaller during period of market stress because investors tend to mimic the action of others. Therefore, statistically significantly negative values of $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ indicate the presence of herding.

Chang et al. (2000) develop an alternative method in spirit of Christie and Huang (1995) model. They define CSAD as follows:

$$\boldsymbol{CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|} \tag{5}$$

Where $\boldsymbol{R_{m,\,t}}$ is the cross-sectional average returns of N stocks in the portfolio at time t and $\boldsymbol{R_{i,\,t}}$ is the return of stock i at time t. The return of individual stock at time t is calculated as $\boldsymbol{R_{i,\,t} = 100\ x\ (\ln(P_t) - \ln(P_{t-1}))}$, where $P_t$ and $P_{t\text{-}1}$ is the closing price at time t and t-1, respectively.

According to the rational asset pricing model, they assert that the relationship between return dispersions and market returns is linear. However, during periods of relatively large price movement, the linear relationship becomes non-linear increasing or even decreasing if herding exists. Hence, Chang et al. (2000) add the quadratic term of $\boldsymbol{R_{m,\,t}}$ to the regression model to measure the non-linearity as follows:

$$\boldsymbol{CSAD_t = \gamma_0 + \gamma_1\ |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t} \tag{6}$$

The relationship between $\boldsymbol{CSAD_t}$ and $\boldsymbol{R_{m,\,t}}^{\boldsymbol{2}}$ contributes to recognizing herding. Thus, a negative and statistically significant of coefficient $\gamma_2$ implies the decrease of return dispersion from market returns which indicates the presence of herding.

If herding exists during different extreme market movements, the relationship between CSSD and market return can also be non-linear (Huang et al., 2015). Therefore, this paper adopts the following supplementary regression models:

$$\boldsymbol{CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t} \tag{7}$$

$$\boldsymbol{CSSD_t = \gamma_0 + \gamma_1\ |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t} \tag{8}$$

In conclusion, this study investigates herding by employing two models as follows:

$$\boldsymbol{DepVari_{i,t} = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t} \tag{9}$$

$$\boldsymbol{DepVari_{i,t} = \gamma_0 + \gamma_1\ |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t} \tag{10}$$

where $\boldsymbol{DepVari_{i,\,t}}$ is the dependent variable of the regression equation, i denotes CSSD or CSAD. Other variables are defined as in the previous description.

In addition, we use the following empirical equations to examine asymmetric effect of herding under up and down markets:

$$\boldsymbol{DepVari_{i,t}^{UP} = \gamma_0 + \gamma_1{}^{UP}\ |R_{m,t}^{UP}| + \gamma_2{}^{UP}(R_{m,t}^{UP})^2 + \varepsilon_t} \tag{11}$$

$$\boldsymbol{DepVari_{i,t}^{DOWN} = \gamma_0 + \gamma_1{}^{DOWN}\ |R_{m,t}^{DOWN}| + \gamma_2{}^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon_t} \tag{12}$$

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

## 4. Regression results

### 4.1. Descriptive statistics

Table 1 presents the summary of descriptive statistics of returns dispersion measured by CSSD and CSAD for the full sample period

**Table 1**
Descriptive statistics.

| | Mean | Std. Dev | Min | Max | Obs |
|---|---|---|---|---|---|
| Full sample period | | | | | |
| $CSSD_t$ | 2.0974 | 0.8145 | 0.0608 | 9.2542 | 2883 |
| $CSAD_t$ | 1.6132 | 0.7221 | 0.0282 | 7.3013 | 2883 |
| BFC period | | | | | |
| $CSSD_t$ | 2.3680 | 0.4280 | 0.0805 | 9.2542 | 1886 |
| $CSAD_t$ | 1.7491 | 0.4141 | 0.0804 | 3.1412 | 1886 |
| FC period | | | | | |
| $CSSD_t$ | 1.9554 | 0.8321 | 0.3149 | 3.9709 | 377 |
| $CSAD_t$ | 1.6194 | 0.8126 | 0.0393 | 3.3432 | 377 |
| AFC period | | | | | |
| $CSSD_t$ | 1.3604 | 1.1537 | 0.0608 | 7.4937 | 620 |
| $CSAD_t$ | 1.1959 | 1.1286 | 0.0282 | 7.3013 | 620 |

The table presents the descriptive statistics of return dispersion measured by CSSD and CSAD for four periods including the full sample period, before crisis period (BFC), financial crisis period (FC) and after crisis period (AFC). The mean is the average value, the Std.Dev is the standard deviation, the Min and Max are the minimum and maximum return dispersion, respectively. The Obs is the number of trading observations in sample. The time period covers from January 2005 to July 2016.

and three sub-periods. The mean values of both CSSD and CSAD in four periods are all greater than zero, which reveals that individual stock returns and market returns do not move simultaneously. Furthermore, the values decreasing over time from BFC period to AFC period preliminarily indicate that herding is likely to be more pronounced in AFC period than in other periods. In addition, the increasing standard deviations representing the variability of return dispersion from BFC period to AFC period reflect there are more different investing patterns among investors in AFC period.

### *4.2. Regression results*

We begin with the investigation of herding in different periods and the results are shown in Table 2. Panel A reports the estimated results when applying Eq. (9) with $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are dummy variables to measure herding in extremely upper and lower tails of the distribution. We choose 1% and 5% criteria as the restrict of $\boldsymbol{D_t}^{\boldsymbol{L}}$ and $\boldsymbol{D_t}^{\boldsymbol{U}}$ according to the arbitrary definition of extreme market conditions suggested by Christie and Huang (1995). The estimates of $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ for CSSD and CSAD in both criterion levels are significant positive in all periods. The result simply that stock return dispersion tends to increase over periods of extreme price movement, which does not support the presence of herding for the whole sample and each sub-periods.

We proceed to duplicate the investigation by employing Eq. (10) and the results are summarized in panel B of Table 2. The positive and significant coefficients $\gamma_1$ indicate the linear relationship between the dependent variables and independent variables, which is consistent with the prediction of rational asset pricing model. The herding coefficients $\gamma_2$ are somewhat different between two dependent variables CSSD and CSAD. More specifically, our results report the significantly positive or insignificantly negative herding coefficients, which indicate no evidence of herding when regressing the model with return dispersion measured by CSSD. However, our results reveal the quadratic non-linearity between market returns and return dispersion measured by CSAD through the significantly negative coefficients of squared terms ($\gamma_2$). This finding provides empirical evidence of the existence of herding propensity in Vietnam stock market covering the whole period from 2005 to 2016 and over all sub-periods including pre-crisis (BFC), during crisis (FC), and post-crisis (AFC). This conclusion is consistent with results in recent studies regarding the presence of herding in emerging markets (Dang and Lin, 2016; Vo and Phan, 2017).

The difference in results between CSSD and CSAD arises from the condition of application. Christie and Huang (1995) propose CSSD method to measure herding in extremely large price swing rather than in normal periods; however, the definition of extreme market movements is very arbitrary. Besides, CSSD model is based on linear terms while herding involves non-linearity (Bensaida, 2017). Moreover, the estimated results show that the non-linear model provides a better fit for data and the adjusted R-squared of CSAD are much higher than those of CSSD across periods. Therefore, the two methods are in analogous spirit but do not reach the same conclusion.

We then examine whether herding exists in different groups of idiosyncratic volatility under different timeframe. We divide all stocks into three groups according to the level of idiosyncratic volatility of each specific firm. Group 1 includes stocks with the smallest idiosyncratic volatility, group 3 comprises stocks with the largest idiosyncratic volatility and group 2 consists of the rest stocks. Our paper employs both CSSD and CSAD method to detect herding in three portfolios sorting by individual stock's idiosyncratic volatility over four periods. The estimated results are reported in Table 3. Panel A of Table 3 reports results when applying Eq. (9) with dependent variables CSSD and CSAD. The results show that the coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are positive in all periods within three levels of idiosyncratic volatility; thus, implicating that individual stocks move further from the market consensus leading to the increase in dispersion. This result is contradictory with the definition of herding which requires the decrease rather than the increase.

In panel B, we run the regression of Eq. (10) to estimate herding within different groups of idiosyncratic volatility. We also separate the sample into three sub-periods including pre-crisis (BFC), during crisis (FC) and post-crisis (AFC) to deeply analyze the

**Table 2**
Regression results of CSSD and CSAD approach for full sample period and three sub-periods.

| | Full sample period | | BFC period | | FC period | | AFC period | |
|---|---|---|---|---|---|---|---|---|
| | CSSD | CSAD | CSSD | CSAD | CSSD | CSAD | CSSD | CSAD |
| Panel A: The estimation results of Eq. (9) | | | | | | | | |
| 1% criterion | | | | | | | | |
| α | 2.058*** | 1.574*** | 1.258*** | 1.094*** | 1.849*** | 1.528*** | 2.378*** | 1.739*** |
| | (141.33) | (123.72) | (30.15) | (26.92) | (49.23) | (39.92) | (271.08) | (206.38) |
| $\beta_1$ | 1.782*** | 1.704*** | 3.188*** | 3.136*** | 1.926*** | 1.673*** | 1.129*** | 0.981*** |
| | (12.76) | (13.96) | (8.21) | (8.28) | (9.98) | (8.50) | (8.90) | (8.05) |
| $\beta_2$ | 1.748*** | 1.798*** | 2.863*** | 2.859*** | 1.885*** | 1.563*** | 1.073*** | 1.07*** |
| | (12.71) | (14.97) | (10.36) | (10.62) | (6.97) | (5.67) | (8.87) | (9.25) |
| $Adj-R^2$ | 0.099 | 0.125 | 0.215 | 0.222 | 0.275 | 0.722 | 0.069 | 0.07 |
| 5% criterion | | | | | | | | |
| α | 1.962*** | 1.462*** | 1.014*** | 0.848*** | 1.609*** | 1.282*** | 2.343*** | 1.689*** |
| | (138.67) | (128.21) | (31.08) | (27.50) | (54.17) | (44.04) | (273.54) | (225.73) |
| $\beta_1$ | 1.261*** | 1.389*** | 2.573*** | 2.566*** | 1.666*** | 1.619*** | 0.688*** | 0.882*** |
| | (21.24) | (29.01) | (18.71) | (19.72) | (21.16) | (20.99) | (15.34) | (22.52) |
| $\beta_2$ | 1.232*** | 1.406*** | 2.535*** | 2.548*** | 1.4776*** | 1.446*** | 0.642*** | 0.855*** |
| | (20.82) | (29.47) | (23.09) | (24.54) | (15.77) | (15.75) | (14.04) | (21.41) |
| $Adj-R^2$ | 0.225 | 0.360 | 0.571 | 0.599 | 0.624 | 0.621 | 0.165 | 0.310 |
| Panel B: The estimation results of Eq. (10) | | | | | | | | |
| α | 1.673*** | 0.997*** | 0.299*** | 0.096*** | 1.131*** | 0.516*** | 2.270*** | 1.386*** |
| | (71.24) | (62.54) | (13.04) | (9.58) | (24.69) | (15.03) | (148.22) | (131.06) |
| $\gamma_1$ | 0.299*** | 0.574*** | 0.940*** | 1.003*** | 0.369*** | 0.762*** | 0.035 | 0.427*** |
| | (9.16) | (25.92) | (30.69) | (74.49) | (7.08) | (19.79) | (1.46) | (25.99) |
| $\gamma_2$ | 0.038*** | −0.011* | −0.008 | −0.020*** | 0.050*** | −0.035*** | 0.050*** | −0.025*** |
| | (4.79) | (−1.93) | (0.27) | (−6.53) | (4.40) | (−4.19) | (7.83) | (−5.58) |
| $Adj-R^2$ | 0.339 | 0.613 | 0.914 | 0.983 | 0.803 | 0.887 | 0.222 | 0.596 |

Panel A presents the estimation results for the full sample period and three sub-periods of Eq. (9)$DepVari_{i,\ t} = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t$ where $DepVari_{i,\ t}$ is dependent variable, the subscript i denotes CSSD or CSAD measure. $D_t^L$ and $D_t^U$ are dummy variables taking the unity value if the return on the market for time period t lies in the extreme lower tail and extremely upper tail of the returns distribution, respectively, and zero otherwise. The criterion for extreme condition is at 1% and 5% of the market return observations. Panel B provides estimation results of Eq. (10) $DepVari_{i,\ t} = \gamma_0 + \gamma_1 |R_{m,\ t}| + \gamma_2 R_{m,\ t}^2 + \varepsilon_t$ where $R_{m,\ t}$ is the market return and $R_{m,\ t}^2$ is the quadratic term of $R_{m,\ t}$. The sample period is from 2005 to 2016. The symbol (***) denotes the significant level at 1% level.

impact of extreme events on herding within different levels of idiosyncratic volatility. Similarly, the results of all herding coefficients measured by CSSD method are positive or insignificantly negative which imply no evidence supports the presence of herding for the whole sample and each sub-period. Using CSAD method, the results are completely different. For the full sample period, the herding coefficient is significant and positive in most of groups except for group 1. This result implies that herding only displays in stock portfolio with smallest idiosyncratic volatility. In each sub-period, the coefficients $\gamma_2$are all negative and significant at the highest level, which indicate the presence of herding across periods and groups. This supportive evidence is consistent with the results in Table 2.

We next examine the asymmetric effect of herding in up and down markets with different levels of idiosyncratic volatility. In this investigation, we utilize non-linear model developed by Chang et al. (2000) for four periods analyzed. The results are shown in Table 4. Most of herding coefficients of ($\gamma_2$) are significantly negative in four periods within three groups of idiosyncratic volatility except for some cases. More specifically, in the full sample, all coefficients of quadratic terms are found to be insignificant suggesting that no evidence supports the decrease of return dispersion in rising market. The results; in contrast, confirms the homogeneous trading behavior on days when the market is down within three stock portfolios. In each sub-period, the insignificantly negative of herding coefficient in group 3 during financial crisis indicates that herding does not exist in up market condition. The findings reflect the fact that during global financial meltdown, numerous individual investors limit their trading of stocks with high idiosyncratic volatility because of their loss-averse sentiment.

We also compare the level of herding between group 1 and group 3 by using the *t*-test (G1-G3) and the results are shown in the last column of Table 4. The significant disparity between two groups for the whole sample period and post-crisis period indicates that herding in group with smallest idiosyncratic volatility is stronger than that in group with largest idiosyncratic volatility. We find no evidence for the differences between two groups in AFC and FC period. Furthermore, we duplicate the t-test to compare the herding coefficients $\gamma_2^{UP}$ and $\gamma_2^{DOWN}$ under up and down market within three groups. The results reveal that herding tend to be more pronounced in declining market than in rising market; however, the asymmetric response only displays in pre-crisis and post-crisis periods.

We finally analyze herding within industries; in particular, we examine whether herding occurs in different periods. In this paper, we focus on two industries and one sector which have gained the attention from both investors and policy makers. They include financial industry, technology industry and banking sector of the financial industry according to the classification of Ho Chi Minh stock exchange. We employ Eqs. (11) and (12) to run the regression for up and down markets, respectively. Table 5 presents the

**Table 3**
The regression results of CSSD and CSAD under various levels of idiosyncratic volatility.

| | | Panel A: The results of Eq. (9) | | | | | | Panel B: The results of Eq. (10) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1% criterion | | | 5% criterion | | | | | |
| | | $\beta_1$ | $\beta_2$ | Adj-$R^2$ | $\beta_1$ | $\beta_2$ | Adj-$R^2$ | $\gamma_1$ | $\gamma_2$ | Adj-$R^2$ |
| Full sample period | | | | | | | | | | |
| Group 1 | CSSD | 1.770*** | 1.652*** | 0.067 | 1.182*** | 1.221*** | 0.256 | 0.315*** | 0.032*** | 0.383 |
| | | (9.67) | (10.81) | | (22.52) | (23.45) | | (10.77) | (4.53) | |
| | CSAD | 1.476*** | 1.494*** | 0.068 | 1.280*** | 1.271*** | 0.386 | 0.578*** | −0.021*** | 0.665 |
| | | (9.32) | (11.30) | | (31.00) | (31.05) | | (30.59) | (−4.49) | |
| Group 2 | CSSD | 1.782*** | 1.703*** | 0.058 | 1.137*** | 1.167*** | 0.198 | 0.227**** | 0.048*** | 0.289 |
| | | (9.18) | (10.51) | | (19.79) | (20.49) | | (7.04) | (5.98)) | |
| | CSAD | 1.641*** | 1.731*** | 0.073 | 1.338*** | 1.322*** | 0.347 | 0.516*** | −0.003 | 0.566 |
| | | (9.75) | (12.31) | | (29.51) | (29.42) | | (23.45) | (0.58) | |
| Group 3 | CSSD | 1.759*** | 1.560*** | 0.04 | 1.060*** | 1.095*** | 0.13 | 0.257*** | 0.035*** | 0.20 |
| | | (7.76) | (8.24) | | (15.35) | (15.99) | | (6.38) | (3.63) | |
| | | | | 1 | | | 7 | | | 8 |
| | CSAD | 1.637*** | 1.658*** | 0.058 | 1.269*** | 1.275*** | 0.267 | 0.530*** | −0.009 | 0.449 |
| | | (8.59) | (10.41) | | (23.49) | (23.79) | | (18.53) | (−1.30) | |
| BFC period | | | | | | | | | | |
| Group 1 | CSSD | 3.186*** | 2.658*** | 0.116 | 2.287*** | 2.302*** | 0.529 | 0.889*** | −0.012 | 0.833 |
| | | (5.23) | (7.52) | | (21.19) | (17.40) | | (21.49) | (−1.26) | |
| | CSAD | 2.961*** | 2.567*** | 0.120 | 2.265*** | 2.246*** | 0.583 | 0.969*** | −0.031*** | 0.958 |
| | | (5.19) | (7.76) | | (23.78) | (19.24) | | (50.10) | (−6.91) | |
| Group 2 | CSSD | 2.890*** | 3.395*** | 0.128 | 2.508*** | 2.480*** | 0.588 | 0.940*** | −0.008 | 0.912 |
| | | (7.99) | (5.44) | | (19.68) | (23.85) | | (30.28) | (−1.14) | |
| | CSAD | 2.884*** | 3.349*** | 0.132 | 2.499*** | 2.495*** | 0.619 | 1.003*** | −0.021*** | 0.982 |
| | | (8.18) | (5.51) | | (25.57) | (20.83) | | (72.92) | (−6.53) | |
| Group 3 | CSSD | 3.393*** | 2.784*** | 0.114 | 2.473*** | 2.476*** | 0.548 | 0.948*** | −0.011 | 0.854 |
| | | (5.25) | (7.43) | | (22.09) | (18.05) | | (23.17) | (−1.18) | |
| | CSAD | 3.256*** | 2.784*** | 0.124 | 2.475*** | 2.467*** | 0.612 | 0.998*** | −0.021*** | 0.973 |
| | | (5.36) | (7.90) | | (25.21) | (20.50) | | (60.24) | (−5.62) | |
| FC period | | | | | | | | | | |
| Group 1 | CSSD | 1.699*** | 1.533*** | 0.156 | 1.244*** | 1.445*** | 0.569 | 0.269*** | 0.053*** | 0.683 |
| | | (6.33) | (5.71) | | (13.65) | (19.25) | | (4.43) | (3.95) | |
| | CSAD | 1.083*** | 1.266*** | 0.094 | 1.150*** | 1.341*** | 0.568 | 0.660*** | −0.038*** | 0.768 |
| | | (4.20) | (4.91) | | (13.61) | (19.25) | | (13.70) | (−3.63) | |
| Group 2 | CSSD | 1.949*** | 1.824*** | 0.183 | 1.449*** | 1.629*** | 0.634 | 0.364*** | 0.049*** | 0.793 |
| | | (6.84) | (6.40) | | (15.97) | (21.79) | | (6.87) | (4.30) | |
| | CSAD | 1.625*** | 1.497*** | 0.131 | 1.416*** | 1.586*** | 0.636 | 0.757*** | −0.036*** | 0.880 |
| | | (5.68) | (5.23) | | (16.09) | (21.87) | | (19.24) | (−4.19) | |
| Group 3 | CSSD | 2.016*** | 1.881*** | 0.184 | 1.470*** | 1.665*** | 0.624 | 0.320*** | 0.061*** | 0.778 |
| | | (6.89) | (6.43) | | (15.58) | (21.42) | | (5.70) | (5.02) | |
| | CSAD | 1.779*** | 1.657*** | 0.146 | 1.487*** | 1.678*** | 0.653 | 0.738*** | −0.024*** | 0.898 |
| | | (6.03) | (5.62) | | (16.66) | (22.81) | | (19.63) | (−2.99) | |
| AFC period | | | | | | | | | | |
| Group 1 | CSSD | 1.285*** | 1.041*** | 0.040 | 0.697*** | 0.776*** | 0.178 | 0.038*** | 0.122*** | 0.250 |
| | | (6.74) | (5.90) | | (13.64) | (15.57) | | (5.08) | (4.37) | |
| | CSAD | 0.967*** | 0.776*** | 0.032 | 0.824*** | 0.876*** | 0.340 | 0.478*** | −0.038*** | 0.660 |
| | | (6.05) | (5.24) | | (21.53) | (23.46) | | (30.47) | (−8.96) | |
| Group 2 | CSSD | 1.197*** | 1.077*** | 0.047 | 0.631*** | 0.678*** | 0.174 | 0.066*** | 0.044*** | 0.237 |
| | | (7.04) | (6.83) | | (13.72) | (15.12) | | (2.61) | (6.48) | |
| | CSAD | 0.952*** | 0.991*** | 0.038 | 0.820*** | 0.851*** | 0.312 | 0.446*** | −0.031*** | 0.594 |
| | | (5.83) | (6.55) | | (20.44) | (21.76) | | (25.34) | (−6.52) | |
| Group 3 | CSSD | 1.171*** | 0.902*** | 0.029 | 0.503*** | 0.542*** | 0.082 | 0.014 | 0.044*** | 0.109 |
| | | (5.88) | (4.89) | | (8.96) | (9.91) | | (0.47) | (5.22) | |
| | CSAD | 0.948*** | 0.963*** | 0.028 | 0.732*** | 0.764*** | 0.195 | 0.397*** | −0.026*** | 0.374 |
| | | (5.11) | (5.61) | | (14.93) | (15.99) | | (16.08) | (−4.01) | |

Panel A presents the estimation results for the full sample period and three sub-periods of Eq. (9)$\boldsymbol{DepVari_{i,\ t}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1 D_t^L} + \boldsymbol{\beta_2 D_t^U} + \boldsymbol{\varepsilon_t}$ where $\boldsymbol{DepVari_{i,\ t}}$ is dependent variable, the subscript i denotes CSSD or CSAD measure. $\boldsymbol{D_t^L}$and$\boldsymbol{D_t^U}$ are dummy variables taking the unity value if the return on the market for time period t lies in the extreme lower tail and extremely upper tail of the returns distribution, respectively, and zero otherwise. The criterion for extreme condition is at 1% and 5% of the market return observations. Panel B provides estimation results of Eq. (10)$\boldsymbol{DepVari_{i,\ t}} = \gamma_0 + \gamma_1 |\boldsymbol{R_{m,\ t}}| + \gamma_2 \boldsymbol{R_{m,\ t}}^2 + \boldsymbol{\varepsilon_t}$ where $\boldsymbol{R_{m,\ t}}$ is the market return and $\boldsymbol{R_{m,\ t}}^2$ is the quadratic term of $\boldsymbol{R_{m,\ t}}$. This research sorts the sample into three groups based on the yearly idiosyncratic volatility of individual stocks. Group 1 consists of stocks with the smallest idiosyncratic volatility and group 3 includes stocks with the largest idiosyncratic volatility. The sample period is from 2005 to 2016. The symbol (***) denotes the significant level at 1% level.

**Table 4**
Asymmetric effect in up and down markets within different levels of idiosyncratic volatility.

| | Group 1 | | Group 2 | | Group 3 | | G1-G3 | |
|---|---|---|---|---|---|---|---|---|
| | CSSD | CSAD | CSSD | CSAD | CSSD | CSAD | CSSD | CSAD |
| Full sample period | | | | | | | | |
| Up market | | | | | | | | |
| $\gamma_1^{UP}$ | 0.294*** | 0.531*** | 0.272*** | 0.514*** | 0.232*** | 0.478*** | 0.062*** | 0.053*** |
| | (8.35) | (20.95) | (6.31) | (17.07) | (4.24) | (12.39) | (−13.61) | (−12.23) |
| $\gamma_2^{UP}$ | 0.040*** | −0.004 | 0.045*** | 0.006 | 0.043*** | 0.007 | −0.003*** | 0.038*** |
| | (4.68) | (−0.73) | (4.30) | (0.91) | (3.23) | (0.81) | (−13.61) | (−12.23) |
| Adj-$R^2$ | 0.444 | 0.667 | 0.345 | 0.610 | 0.207 | 0.457 | | |
| Down market | | | | | | | | |
| $\gamma_1^{DOWN}$ | 0.342*** | 0.632*** | 0.323*** | 0.623*** | 0.287*** | 0.591*** | 0.055*** | −0.268*** |
| | (7.18) | (22.44) | (6.44) | (18.53) | (4.79) | (13.88) | (−11.71) | (−12.10) |
| $\gamma_2^{DOWN}$ | 0.023** | −0.038*** | 0.027** | −0.029*** | 0.027** | −0.027*** | −0.004*** | −0.011*** |
| | (1.98) | (−5.57) | (2.26) | (−3.63) | (1.88) | (−2.65) | (−11.72) | (−12.11) |
| Adj-$R^2$ | 0.333 | 0.646 | 0.310 | 0.583 | 0.208 | 0.443 | | |
| $\gamma_2^{UP}$-$\gamma_2^{DOWN}$ | 0.017 | 0.034 | 0.018 | 0.035 | 0.016 | 0.034 | | |
| | (−0.83) | (0.73) | (−0.49) | (0.45) | (−0.17) | (0.19) | | |
| BFC period | | | | | | | | |
| Up market | | | | | | | | |
| $\gamma_1^{UP}$ | 0.858*** | 0.929*** | 0.919*** | 0.978*** | 0.921*** | 0.966*** | −0.063 | −0.037 |
| | (22.52) | (42.87) | (30.47) | (63.33) | (24.23) | (51.67) | (0.22) | (−0.18) |
| $\gamma_2^{UP}$ | −0.003 | −0.019*** | −0.002 | −0.014*** | −0.003 | −0.012*** | −0.000 | −0.006 |
| | (−0.41) | (−4.09) | (−0.42) | (−4.12) | (−0.42) | (−3.14) | (0.23) | (−0.19) |
| Adj-$R^2$ | 0.905 | 0.967 | 0.946 | 0.985 | 0.917 | 0.978 | | |
| Down market | | | | | | | | |
| $\gamma_1^{DOWN}$ | 0.997*** | 1.092*** | 1.010*** | 1.076*** | 1.046*** | 1.091*** | −0.049 | 0.001 |
| | (10.66) | (28.80) | (14.76) | (39.64) | (11.35) | (33.67) | (0.36) | (−0.05) |
| $\gamma_2^{DOWN}$ | −0.039* | −0.064*** | −0.025 | −0.040*** | −0.036 | −0.046*** | −0.003 | −0.018 |
| | (−1.72) | (−6.93) | (−1.51) | (−6.07) | (−1.61) | (−5.88) | (0.37) | (−0.06) |
| Adj-$R^2$ | 0.745 | 0.947 | 0.864 | 0.976 | 0.776 | 0.966 | | |
| $\gamma_2^{UP}$-$\gamma_2^{DOWN}$ | 0.036** | 0.045*** | 0.023** | 0.026*** | 0.003* | 0.034*** | | |
| | (1.77) | (2.65) | (2.09) | (2.67) | (1.83) | (2.60) | | |
| FC period | | | | | | | | |
| Up market | | | | | | | | |
| $\gamma_1^{UP}$ | 0.165*** | 0.594*** | 0.256*** | 0.691*** | 0.224** | 0.679*** | −0.059 | −0.423 |
| | (1.68) | (7.60) | (2.91) | (10.70) | (2.51) | (11.19) | (−0.85) | (−0.97) |
| $\gamma_2^{UP}$ | 0.067** | −0.033* | 0.067*** | −0.028* | 0.077*** | −0.018 | −0.010 | 0.085 |
| | (3.02) | (−1.87) | (3.36) | (−1.94) | (3.77) | (−1.33) | (−0.90) | (−0.97) |
| Adj-$R^2$ | 0.598 | 0.702 | 0.726 | 0.845 | 0.727 | 0.872 | | |
| Down market | | | | | | | | |
| $\gamma_1^{DOWN}$ | 0.365*** | 0.731*** | 0.458*** | 0.821*** | 0.406*** | 0.797*** | −0.041 | −0.066 |
| | (4.75) | (12.11) | (7.02) | (16.85) | (5.61) | (16.81) | (−1.17) | (−1.45) |
| $\gamma_2^{DOWN}$ | 0.038** | −0.046*** | 0.034** | −0.044*** | 0.048*** | −0.032*** | −0.010 | −0.014 |
| | (2.33) | (−3.64) | (2.50) | (−4.32) | (3.13) | (−3.21) | (−1.18) | (−1.46) |
| Adj-$R^2$ | 0.738 | 0.812 | 0.837 | 0.903 | 0.811 | 0.916 | | |
| $\gamma_2^{UP}$-$\gamma_2^{DOWN}$ | 0.029 | 0.013 | 0.033 | 0.016 | 0.029 | 0.014 | | |
| | (−0.67) | (−0.91) | (−0.86) | (−1.13) | (−0.93) | (−1.22) | | |
| AFC period | | | | | | | | |
| Up market | | | | | | | | |
| $\gamma_1^{UP}$ | 0.121*** | 0.482*** | 0.050 | 0.424*** | −0.002 | 0.367*** | 0.123*** | 0.115*** |
| | (4.11) | (21.66) | (1.47) | (16.36) | (−0.06) | (9.890 | (−30.56) | (−24.70) |
| $\gamma_2^{UP}$ | 0.038*** | −0.039*** | 0.049*** | −0.023*** | 0.048*** | −0.017* | −0.010*** | −0.022*** |
| | (4.70) | (−6.46) | (5.22) | (−3.32) | (3.60) | (−1.74) | (−30.67) | (−24.71) |
| Adj-$R^2$ | 0.372 | 0.664 | 0.257 | 0.584 | 0.089 | 0.352 | | |
| Down market | | | | | | | | |
| $\gamma_1^{DOWN}$ | 0.129*** | 0.479*** | 0.082*** | 0.466*** | 0.034 | 0.425*** | 0.095*** | 0.054*** |
| | (2.75) | (21.38) | (2.20) | (19.26) | (0.83) | (12.80) | (−23.76) | (−23.47) |
| $\gamma_2^{DOWN}$ | 0.035*** | −0.037*** | 0.037** | −0.036*** | 0.039*** | −0.034*** | −0.004*** | −0.003*** |
| | (2.90) | (−6.39) | (3.92) | (−5.85) | (3.64) | (−3.97) | (−23.77) | (−23.47) |
| Adj-$R^2$ | 0.193 | 0.657 | 0.220 | 0.605 | 0.131 | 0.399 | | |
| $\gamma_2^{UP}$-$\gamma_2^{DOWN}$ | 0.003*** | −0.002 | 0.012*** | 0.013 | 0.009* | 0.017* | | |
| | (−2.79) | (−0.94) | (−2.92) | (−1.51) | (−1.79) | (−1.73) | | |

This table provides the estimation results for the full sample period and three sub-periods under various market conditions. The specifications follow Eq. (11) $\boldsymbol{DepVari}_{i,t}^{UP} = \gamma_0 + \gamma_1^{UP}\,|\boldsymbol{R}_{m,t}^{UP}| + \gamma_2^{UP}(\boldsymbol{R}_{m,t}^{UP})^2 + \varepsilon_t$ and Eq. (12) $\boldsymbol{DepVari}_{i,t}^{DOWN} = \gamma_0 + \gamma_1^{DOWN}\,|\boldsymbol{R}_{m,t}^{DOWN}| + \gamma_2^{DOWN}(\boldsymbol{R}_{m,t}^{DOWN})^2 + \varepsilon_t$ where ***DepVari*** is the dependent variable, i denotes CSSD or CSAD.$|\boldsymbol{R}_{m,\,t}{}^{UP}|$ and $|\boldsymbol{R}_{m,\,t}{}^{DOWN}|$ are the absolute values of average market returns in up and down markets, respectively. $(\boldsymbol{R}_{m,\,t}{}^{UP})^2$and $(\boldsymbol{R}_{m,\,t}{}^{DOWN})^2$ are corresponding quadratic terms. This research sorts the sample into three groups based on the yearly idiosyncratic volatility of individual stocks. Group 1 consists of stocks with the smallest idiosyncratic volatility and group 3 includes stocks with the largest idiosyncratic volatility. This paper also tests the different between group 1 and group 3 by using t-test (G1-G3). The sample period is from 2005 to 2016. The symbol (***), (**) and (*) denote the significant level at 1%, 5% and 10% level, respectively.

**Table 5**
The results of CSAD regression within different industries.

| | Up market | | | Down market | | | T-statistics |
|---|---|---|---|---|---|---|---|
| | $\gamma_1^{UP}$ | $\gamma_2^{UP}$ | Adj-$R^2$ | $\gamma_1^{DOWN}$ | $\gamma_2^{DOWN}$ | Adj-$R^2$ | $\gamma_2^{DOWN}$-$\gamma_2^{UP}$ |
| Financial industry | | | | | | | |
| Full sample | 0.649*** | 0.025*** | 0.780 | 0.732*** | −0.004 | 0.767 | −0.029 |
| | (23.48) | (3.80) | | (23.88) | (−0.65) | | (0.63) |
| BFC period | 0.995*** | −0.0002 | 0.984 | 1.044*** | −0.016* | 0.956 | −0.016** |
| | (56.55) | (−0.08) | | (26.43) | (−1.73) | | (−2.12) |
| FC period | 0.816*** | −0.002 | 0.943 | 0.844*** | −0.003 | 0.933 | −0.001 |
| | (15.61) | (−0.17) | | (15.93) | (−0.29) | | (0.63) |
| AFC period | 0.550*** | 0.011 | 0.628 | 0.642*** | −0.022** | 0.652 | −0.033 |
| | (13.59) | (1.07) | | (17.70) | (−2.42) | | (0.97) |
| Banking sector of the financial industry | | | | | | | |
| Full sample | 0.565*** | 0.032*** | 0.711 | 0.639*** | −0.0002 | 0.676 | −0.034 |
| | (18.38) | (4.34) | | (18.55) | −0.03 | | (0.63) |
| BFC period | 0.993*** | −0.016*** | 0.979 | 1.063*** | −0.035*** | 0.965 | −0.019** |
| | (52.58) | (−4.05) | | (32.12) | (−4.40) | | (−2.13) |
| FC period | 0.566*** | 0.032*** | 0.711 | 0.639*** | −0.0001 | 0.676 | −0.0321 |
| | (18.40) | (4.33) | | (18.32) | (−0.02) | | (0.63) |
| AFC period | 0.387*** | 0.035*** | 0.458 | 0.540*** | −0.031*** | 0.409 | −0.066 |
| | (7.86) | (2.60) | | (11.69) | (−2.61) | | (0.97) |
| Technology industry | | | | | | | |
| Full sample | 0.029** | 0.666*** | 0.555 | 0.612*** | −0.032** | 0.524 | −0.698 |
| | (2.49) | (13.69) | | (11.14) | (2.43) | | (0.63) |
| BFC period | 0.685*** | 0.031*** | 0.599 | 0.612*** | 0.032** | 0.525 | 0.001** |
| | (19.07) | (3.98) | | (11.14) | (2.43) | | (−2.12) |
| FC period | 0.666*** | 0.029** | 0.555 | 0.622*** | 0.030** | 0.528 | 0.001 |
| | (13.69) | (2.49) | | (11.24) | (2.28) | | (0.63) |
| AFC period | 0.509*** | 0.037* | 0.334 | 0.475*** | 0.025 | 0.299 | −0.012 |
| | (6.35) | (1.71) | | (6.11) | (1.29) | | (0.97) |

This table provides the estimation results for the full sample period and three sub-periods under various market conditions within different industries. The specifications follow Eq. (11) $\boldsymbol{DepVari}_{i,t}^{UP} = \gamma_0 + \gamma_1^{UP}\,|\boldsymbol{R}_{m,t}^{UP}| + \gamma_2^{UP}(\boldsymbol{R}_{m,t}^{UP})^2 + \varepsilon_t$ and Eq. (12) $\boldsymbol{DepVari}_{i,t}^{DOWN} = \gamma_0 + \gamma_1^{DOWN}\,|\boldsymbol{R}_{m,t}^{DOWN}| + \gamma_2^{DOWN}(\boldsymbol{R}_{m,t}^{DOWN})^2 + \varepsilon_t$ where ***DepVari*** is the dependent variable, i denotes CSSD or CSAD.$|\boldsymbol{R}_{m,\ t}{}^{UP}|$ and $|\boldsymbol{R}_{m,\ t}{}^{DOWN}|$ are the absolute values of average market returns in up and down markets, respectively. $(R_{m,\ t}{}^{UP})^2$and $(R_{m,\ t}{}^{DOWN})^2$ are corresponding quadratic terms. The sample is sorted into three main groups including financial industry, banking sector of the financial industry and technology industry. The sample period is from 2005 to 2016. The symbol (***) and (*) denote the significant level at 1% and 10% level, respectively.

estimated results. In terms of various market conditions, the herding coefficients of stocks in three industries are significant and negative in most of cases in down markets. This finding implies that individual investors tend to mimic the action of other participants only on days when the market is falling. In addition, herding also exists in banking sector in rising market. In terms of different periods, most of non-linear terms are significantly negative in pre-crisis and post-crisis periods, which implies that individual stocks tend to cluster around the market consensus leading to herding. Interestingly, no empirical evidence of herding is found during crisis period in all cases though this phenomenon exhibits in both before and after crisis. More specially, the result reveals significantly negative herding coefficient with weak level in the full sample in technology industry. This finding reflects the fact that technological firms in Vietnam are still underdeveloped and less attractive to investors. Therefore, we only find weak evidence of herding in this industry in Vietnam stock market.

## 5. Conclusions and implications

### 5.1. Conclusions

A better understanding of herding is an important contribution to financial stability (Clements et al., 2017). This paper investigates the herding behavior of market participants in Vietnam stock market covering the period from 2005 to 2016. We employ two measures of returns dispersion including cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) and two model settings. We find that both models yield inconsistent results in detecting herding propensity. However, only non-linear relationship measured by CSAD method supports the irrational behavior of investors in identifying herding. Moreover, herd behavior displays differently in various market conditions.

Regression results provide evidence supporting the presence of herding in three sub-groups including before, during and after financial crisis within different levels of idiosyncratic volatility of each individual stock. It is noticed that herding is more likely to be stronger in stock portfolio with the smallest idiosyncratic volatility than in group with the largest level. Furthermore, the finding reveals asymmetric effect to news over market stress periods within each idiosyncratic volatility group. In particular, trading behavior tend to be more homogenous on days when the market is down rather than on days when the market is up.

The finding is consistent when examining the existence of herding within industries. Herding propensity has a tendency to be more pronounced in declining market in three investigated industries including financial industry, banking sector and technology industry. However, banking sector also displays herding in rising market. In addition, we find weak evidence of herding in pre-crisis and post-crisis periods while there is no supportive evidence of this propensity during global meltdown period within different investigated industries.

### 5.2. Implications

Idiosyncratic volatility relates to the undiversified firm-specific risk which is in close relation to the information limitation (or the level of transparency in each firm). Jin and Myers (2006) claim that less transparent firms lead to lower level of idiosyncratic volatility so the ability of outside investors to evaluate a specific firm is less accurate; thus, resulting in the mispricing. This argument is explained by the informed trading hypothesis which is analyzed by Aabo et al. (2017). In particular, the informed trading hypothesis predicts that idiosyncratic volatility is negatively correlated with mispricing because firms with high level of idiosyncratic volatility are more likely to associate with informed traders who trace firms' fundamental values (Jin and Myers, 2006).

This paper is of great implications in both academia and practice which is beneficial to academic researchers, investors and policy makers. Firstly, our investigation provides empirical evidence in the context of an emerging market supplementing the existing literature. This study also advocates authors who base their research on the idea of the informed trading hypothesis. Secondly, based on the aforementioned hypothesis, investors should be well-equipped to realize firms with high and low levels of idiosyncratic and make plausible investment decisions even in case of firms with the smallest idiosyncratic volatility level. This would help the stock prices move towards their fundamental values; thus, leading to market efficiency. Finally, policy makers should focus more on enhancing the information transparency of domestic firms to create an equal investment environment for all firms in Vietnam as well as attracting more investment from outside investors.

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## References

Aabo, T., Pantzalis, C., Park, J.C., 2017. Idiosyncratic volatility: An indicator of noise trading? J. Bank. Finan. 75, 136–151.
Arjoon, V., Bhatnagar, C.S., 2017. Dynamic herding analysis in a frontier market. Res. Int. Bus. Financ. 42, 496–508.
Bali, T.G., Cakici, N., 2008. Idiosyncratic volatility and the cross-section of expected returns. J. Financ. Quant. Anal. 43, 29–58.
Beltratti, A., Stulz, R.M., 2012. The credit crisis around the globe: why did some banks perform better? J. Financ. Econ. 105, 1–17.
Bensaida, A., 2017. Herding effect on idiosyncratic volatility in US industries. Financ. Res. Lett. 23, 121–132.
Bikhchandani, S., Sharma, S., 2001. Herd behavior in financial market. IMF Staff. Pap. 47 (3), 279–310.
Chang, E.C., Dong, S., 2006. Idiosyncratic volatility, fundamentals, and institutional herding: evidence from the Japanese stock market. Pac. Basin Financ. J. 14 (2), 135–154.
Chang, E.C., Cheng, J.W., Khorona, A., 2000. An examination of herd behavior in equity markets: an international perspective. J. Bank. Financ. 24 (10), 1651–1779.
Choi, N., Sias, R.W., 2009. Institutional industry herding. J. Financ. Econ. 94 (3), 469–491.
Christie, W., Huang, R.D., 1995. Following the pied piper: do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37.
Clements, A., Hurn, S., Shi, S., 2017. An empirical investigation of herding in the U.S. stock market. Econ. Model. 67, 184–192.
Dang, H.V., Lin, M., 2016. Herd mentality in the stock market: on the role of idiosyncratic participants with heterogenous information. Int. Rev. Financ. Anal. 48, 247–260.
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, 283–295.
Dennis, P.J., Strickland, D., 2009. The Determinants of Idiosyncratic Volatility. Working paper. University of Virgina.
Fernandez, V., 2014. Stock volatility and pension funds under an individual capitalization-based system. J. Bus. Res. 67, 536–541.
Gebka, B., Wohar, M.E., 2013. International herding: does it differ across sectors? J. Int. Financ. Mark. Inst. Money 23, 55–84.
Guney, Y., Kallinterakis, V., Komba, G., 2017. Herding in frontier markets: evidence from African stock exchanges. J. Int. Financ. Mark. Inst. Money 47, 152–175.
Henker, J., Henker, T., Mitsios, A., 2006. Do investors herd intraday in Australian equities? Int. J. Manag. Financ. 2 (3), 196–219.
Hong, G.H., Yi, K.Y., 2006. On the herding behavior of fund managers in the Korean stock market. Asia-Pacific J. Financ. Stud. 35, 1–37.
Hou, K., 2007. Industry information diffusion and the lead-lag effect in stock returns. Rev. Financ. Stud. 20, 1113–1138.
Huang, T.C., Lin, B.H., Yang, T.H., 2015. Herd behavior and idiosyncratic volatility. J. Bus. Res. 68 (4), 763–770.
Jame, R., Tong, Q., 2009. Retail Investor Indutry Herding.
Jin, L., Myers, S.C., 2006. R2 around the world: New theory and new tests. J. Financ. Econ. 79, 257–292.
Lao, P., Singh, H., 2011. Herding behaviour in the Chinese and Indian stock markets. J. Asian Econ. 22 (6), 495–506.
Lee, C.C., Chen, M.P., Hsieh, K.M., 2013. Industry herding and market states: evidence from Chinese stock markets. Quant. Financ. 13 (7), 1091–1113.
Litimi, H., Bensaida, A., Bouraoui, O., 2016. Herding and excessive risk in the American stock market: a sectoral analysis. Res. Int. Bus. Financ. 38, 6–21.
Malkiel, B.G., Xu, Y., 2003. Investigating the behavior of idiosyncratic volatility. J. Bus. 76, 613–644.
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. J. Financ. 42, 483–510.
Nianhang, X., Xuanyu, J., Chan, C.K., Shinong, W., 2017. Analyst herding and stock price crash risk: evidence from China. J. Int. Financ. Manag. Acc. 28 (3), 308–348.
Scharfstein, D.S., Stein, J.C., 1990. Herd behavior and investment. Am. Econ. Rev. 80 (3), 465–479.
Schmitt, N., Westerhoff, F., 2017. Herding behaviour and volatility clustering in financial markets. Quant. Financ. 17 (8), 1187–1203.
Spyrou, S., 2013. Herding in financial markets: a review of the literature. Rev. Behav. Financ. 5 (2), 175–194.
Tan, D., Henker, J., 2010. Idiosyncratic volatility and retail investor preferences in the Australian market. In: Paper Presented to the 23rd Australasian Finance and Banking Conference 2010 Paper. University of New South Wales.
Vo, X.V., Phan, D.B.A., 2016. Herd behavior in emerging equity market: evidence from Vietnam. Asian J. Law Econ. 7 (3), 369–383.
Vo, X.V., Phan, D.B.A., 2017. Further evidence of the herd behavior in Vietnam stock market. J. Behav. Exp. Financ. 13, 33–41.