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**Article**

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## GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

# Herd behavior and firm-specific information

Chaiyuth Padungsaksawasdi<sup>1\*</sup>

**Abstract:** The study shows critical roles of firm-specific information on herd behavior, which is underexplored in prior literature, albeit an increasing impact of firm-specific information on asset pricing. The main finding demonstrates that three of four selected measures of firm-specific information (return residual, return skewness, and information discreteness) are associated with the aggregate herd behavior in the Thai equity market. The return residual delineates the greatest impacts in most cases, especially during the financial turbulence periods. Herd behavior with firm-specific information is observed at all times. More importantly, less corporate transparency, more noise trading, large asymmetric risk, and low liquidity are the main drivers of intentional herd behavior.

**Subjects:** International Finance; Finance; Investment & Securities

**Keywords:** firm-specific information; herd behavior; financial crisis; behavioral finance; Thailand

**Jel:** G14; G40; G41

### 1. Introduction

It is widely known that market risk alone, as suggested by the Capital Asset Pricing Model (CAPM), is ineffective and insufficient to describe an entire development of stock prices. Roles of firm-specific information in asset pricing have been recently gained attention from both academics and practitioners; however, the results remain inconclusive. Easley et al. (2002) support that firm-specific information measured by the probability of informed trading (PIN)<sup>1</sup> affects stock prices, whereas Duarte and Young (2009) and Lai et al. (2014) arguably find the reverse result. At present, herd behavior or a group of participants imitating the trading behavior is a common phenomenon in financial markets

### ABOUT THE AUTHOR

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### PUBLIC INTEREST STATEMENT

This study investigates herd behavior at the aggregate level in the Stock Exchange of Thailand. To be more specific, whether or not firm-specific information is associated with herd behavior. This strand of research has been largely ignored in previous literature. The sample setting is Thailand as retail investors are dominant. This distinguishes from studies in advanced economies in which traders are mostly institutions. Furthermore, Thailand is one of the important emerging markets in Southeast Asia. The main results confirm the existence of herd behavior in the market, especially when considering the impact of noise trading. Herd behavior is stronger during a high volatile environment. Importantly, firms with less corporate transparency, more noise trading, large asymmetric risk, and low liquidity are likely to show herd behavior.

in which traders follow their trades to others without full acknowledgement of self-conscience and complete information. Conceptually, insofar as the aggregate herd behavior model suggested by E. C. Chang et al. (2000) is grounded on the Black's (1972) CAPM, firm-specific information should play a critical role in the herd behavior model.<sup>2</sup> Nevertheless, the study in this area is underexplored.

Many studies indirectly investigate the relationships of stock characteristics and herd activities. For example, Lakonishok et al. (1992) and Choi and Sias (2009) reveal that company's size and type of businesses affect herd behavior. Specifically, based on the portfolio analysis at the industry level, firm characteristics are important to herd behavior in the U.S. equity market (Demirer & Zhang, 2019). However, they find that only firm's size and momentum strategy determine herd behavior, whereas the book-to-market and market beta do not. Economic conditions also influence herd behavior, showing an asymmetric herd behavior with a stronger effect during turmoil periods (Babalos & Stavroyiannis, 2015; Chiang & Zheng, 2010; Klein, 2013). Notwithstanding the above evidence, only a few literatures investigate the impact of firm-specific information on herd behavior in stock markets. For example, Huang et al. (2015) and Vo and Phan (2019) show that a level of idiosyncratic volatility causes different trading patterns in the stock market, including herd behavior. These shed some light on further research opportunities to identify the extent to which firm-specific information plays a critical role in associating with the aggregated herd behavior.

There is an ongoing debate about an information proxy of stock prices whether or not it is informative or noisy. Hence, I introduce only four related measures of firm-specific information that are employed in this study and discussed more in detail in subsequent sections. First, prior literature (Durnev et al., 2004; Ferreira & Laux, 2007; Morck et al., 2000) finds that idiosyncratic volatility is an outcome of information flow. Roll (1988) shows that public firm-specific news information is largely associated with stock nonsynchronicity (low  $R - Squared$  value). Second, Aabo et al. (2017) find that idiosyncratic volatility positively relates to stock mispricing, supporting noise trading. Third, asymmetric information is a typical violated model assumption in finance and economic theories, which causes different trading decisions. Nguyen et al. (2018) propose that return skewness is a proxy of asymmetric risk. The larger the return skewness, the higher the discrepancy of accessible and available information is. Last, illiquidity premium is priced in equity markets. Thus, illiquid stocks, as measured by information discreteness (Da et al., 2014), reflect a large information asymmetry among market participants, triggering a large number of noise traders. In this paper, I employ four measures of firm-specific return variation that are return nonsynchronicity, residual return, return skewness, and information discreteness.

This paper is different from other related studies in three aspects. First, it focuses on measures of firm-specific return variation, which are indirectly and implicitly observed in stock prices, including return nonsynchronicity (a measure of corporate transparency), residual return (a measure of noise trading), return skewness (a measure of information asymmetry), and information discreteness (a measure of stock illiquidity). This distinguishes from the study of Demirer and Zhang (2019), in which firm characteristics are directly found in the company information (i.e., size, book-to-market, past returns). The findings shed new light in the field. Second, empirical models proposed in this study yield better estimations. As the splitting data and multicollinearity problems shown in prior literature are of less concern. Last, I focus on the aggregate level of herd behavior in an emerging equity market rather than on the industry level because it better represents an overall stockholders' trading decision-making. Moreover, the business variety of and the number of listed stocks in the Stock Exchange of Thailand are limited. Most trades concentrate in the SET50 index, accounting for more than 60% of the total market capitalization<sup>3</sup> and the constituent stocks in the SET50 index mainly consist of the Energy&Utilities and Banking stocks, accounting for more than 37% of the total trading value. Galariotisa et al. (2016) suggest that a problem of less frequent trading stocks impacts an inference in herd behavior model; thus, an analysis at the industry level could mislead true herd behavior in the Stock Exchange of Thailand.

The sample setting in this study is the Stock Exchange of Thailand as supported by some stylized facts as follows. First, Chiang and Zheng (2010) show that herd behavior is stronger in the Asian markets than in the U.S. and the Latin markets and Arjoon and Bhatnagar (2017) suggest that herd behavior is likely to be found in a small equity market. These provide a unique research opportunity to examine the aggregate herd behavior in the Thai equity market. Second, various types of investors define different roles in trading strategies (Grinblatt & Keloharju, 2000; Phansatan et al., 2012), which subsequently affect the movement of stock prices. As retail investors are dominant in the Thai stock exchange, the results on the herd behavior potentially differ from advanced equity markets.<sup>4</sup> Moreover, there is scant research about the herd behavior in Thailand. Thus, this paper aims to fill the gap in the literature.

The objective of this paper is to investigate whether or not firm-specific return variations matter for the aggregate herd behavior in Thailand. The main results support such an effect. The findings of firm-specific information are stronger during the negative market periods as well as the financial turbulent periods. Of selected four measures of firm-specific information, the residual return shows the greatest impact on herd behavior in all cases. Thus, noise trading as measured by the residual return from the market model (Aabo et al., 2017; Blitz et al., 2011) is the most important firm-specific information for herd behavior in the Thai equity market. There is neither direct test nor evidence to identify whether herding is intentional or unintentional. The results in this study offer and link possible explanations in this regard. Specifically, less corporate transparency, more noise trading, large asymmetric risk, and low stock liquidity are the main factors to drive intentional herding, while the opposite is true for unintentional herding.

The remainder of this study is presented as follows. Section 2 summarizes pertinent literature on herd behavior at the aggregate level. Section 3 describes data sets used in this study. Section 4 introduces a methodology for empirical tests and Section 5 presents the results. The last section is summary.

## 2. Pertinent literature

There are prolific studies of herd behavior in financial markets, yet no results are conclusive. Spyrou (2013) provides a thought-provoking review about herd behavior in the financial market, by which the herd behavior is classified into three categories, i.e., institutional investor herding, herding in an aggregate market activity, and herding in analyst recommendation.<sup>5</sup> Along with the aim of this study, I provide a brief review on herd behavior at the aggregate market level as below.

Herd behavior is generally defined as a collective group behavior upon, which an individual follows his trades to peers and ignores his own belief and available information. The aggregate herd behavior detection model is pioneered and developed by Christie and Huang (1995) and E. C. Chang et al. (2000), by studying in the U.S. markets. The basic intuition is that information uncertainty causes investors to follow market consensus, especially during extreme market conditions. The herd behavior contributes significantly to market volatility and is highly prominent during negative market and financial crises (Chiang & Zheng, 2010; Eichengreen et al., 1998; Hwang & Salmon, 2004; Laih & Liao, 2013), confirming the asymmetric herd behavior. Later, global studies on the herd behavior are widely documented with mixed results.<sup>6</sup> The results seem to be driven by selected country samples, time periods of study, and employed methodologies.

Unintentional herding occurs when traders possess similar sets of problems and relevant information, so they coincidentally make the same decision. The whole similar action pushes stock prices to be informationally efficient. On the contrary, there is no logical description to explicitly delineate intentional herd behavior, pushing stock prices to be more informationally inefficient. As factors of investor's decision-making in stock trading are uncountable, it is virtually impossible to distinguish between intentional and unintentional herd behaviors. Banerjee (1992) depicts that intentional information-cascade herd behavior is sensitive to a small shock, potentially leading to excessive market volatility, market destabilization, and episodes of bubbles (Spyrou, 2013).

Regarding the relationship between stock characteristics and herd behavior, Lakonishok et al. (1992) and Choi and Sias (2009) show that the size of company and type of businesses affect institutional herd behavior in the U.S. markets. A more recent study conducted by Demirev and Zhang (2019) emphasizes a crucial role of characteristics of firm on herd behavior over the period of 1964–2016 by using the portfolio analysis approach. Interestingly, only firm's size and momentum strategy are considered important factors, not the book-to-market and market beta factors. The business cycle also influences herd behavior, showing an asymmetric herd behavior with a stronger effect during turmoil periods (Babalos & Stavroyiannis, 2015; Chiang & Zheng, 2010; Klein, 2013). Notwithstanding the above evidence, only a few studies investigate an impact of firm-specific information on herd behavior in the stock markets, although the relationship between firm-specific information and stock prices is widely addressed.

A debate on firm-specific information being subsumed into the stock prices has gained attention from both academics and practitioners. In this paper, I discuss four popular measures of firm-specific information that could embed additional information to firm fundamentals, including return synchronicity, residual return, return skewness, and information discreteness.

A proxy of firm-specific information as noise or information to the stock prices is debatable. First, firm-specific news explains large idiosyncratic volatility (low  $R - Squared$ ) of a firm (Roll, 1988) by employing a market model in the U.S. market, which is later opposed by Jiang et al. (2009) and Aabo et al. (2017). Moreover, large idiosyncratic volatility of return dispersion is more similar to noise (Li et al., 2014). Morck et al. (2000) find large return variations driven by a relatively larger amount of informed risk arbitrage activity in advanced economies. This is later supported by the work of Wurgler (2000), Durnev et al. (2003), and Chen et al. (2007), addressing that a sensitivity in the stock prices is associated with firms or countries with large return variations. Thus, the idiosyncratic volatility or  $R - Squared$  is important information for investors' decision-making. Second, Aabo et al. (2017) point out that stock mispricing (or less informative stock) is driven by noise trading as proxied by return residual from an asset pricing model. The large idiosyncratic volatility in the U.S. market is potentially from the presence of speculation by retail traders (Brandt et al., 2010; Campbell et al., 2001). Thus, residuals in the asset pricing model are associated with stock synchronicity, ultimately affecting the behavior of stock prices. Third, it is widely known that return skewness is a proxy of an information asymmetry, in which return jump from a sudden arrival of information might be a cause of skewness and excess kurtosis. Wanidwaranan and Padungsaksawasdi (2020) study an impact of return jump on herd behavior in a global equity market and find that an information cascade from the return jump well explains the herd behavior. Moreover, the herd behavior is more prevalent when return jumps occur, demonstrating that there is an asymmetry of information affect herd behavior. Last, Da et al. (2014) and R. P. Chang et al. (2018) employ information discreteness as a proxy of investor underreaction/overreaction. They investigate how investors respond to an occurrence of information, in which rational investors promptly take a trading decision when news arrives and irrational investors delay the decision as explained by frog-in-the-pan hypothesis. Moreover, they find that momentum profits depend on the arrival of continuous information. Low information discreteness stocks associate with low investor attention and strong return momentum (Lin et al., 2016). Thus, information discreteness leads to return discontinuity, which reflects an illiquidity of stocks.

### 3. Data

This paper uses daily stock prices from DataStream from January 1987 to December 2019. A total of 849 listed and delisted companies are included. I select the Stock Exchange of Thailand (SET) as the sample setting in this study for several reasons. First, the Thai equity market as one of the fastest growing stock markets in Asia has grown in terms of the number of listed companies, trading volumes, and market capitalizations since its inception in 1975, which calls attention from different traders around the globe. Thus, understanding trading behavior in the Thai stock market is necessary and important for international portfolio diversification. Second, retail investors are dominant players in the SET, which is different from developed markets underlined by a dominance of institutional traders. This proves appropriate for studying herd behavior at the aggregate level that provides

insights for developing markets. Third, Chiang and Zheng (2010) show that herd behavior is stronger in the Asian markets than that in the U.S. and the Latin markets, respectively, whereas Arjoon and Bhatnagar (2017) suggest that herd behavior is likely to be found in a small equity market. These leave room for further research on examining the aggregate herd behavior in the Thai equity market. Last, the business variety of and the number of listed stocks in the SET are limited. Most trades concentrate in the SET50 index, accounting for more than 60% of the total market capitalization. Additionally, the constituent stocks in the SET50 index mainly consist of stocks in the Energy&Utilities and Banking industries, accounting for more than 37% of the total trading value. Galariotisa et al. (2016) suggest that a problem of less frequent trading stocks impacts an inference in herd behavior; thus, an analysis at the industry level could mislead the true herd behavior in the SET. In summary, these unique characteristics of the Thai equity market lie the essential foundation for exploring the existence of herd behavior and provide an additional evidence in the context of international equity markets.

#### 4. Methodology

##### 4.1. Firm-specific information

Selected four types of monthly firm-specific information are computed by using daily individual stock returns (except the residual returns)<sup>7</sup> over the entire sample period as follows.

First, the monthly return nonsynchronicity ( $NSYNC_t$ ) suggested by Dasgupta et al. (2010) is measured by the logistic transformation of the coefficient of determination ( $R - Squared$ ) of the market model.<sup>8</sup> Dasgupta et al. (2010) suggest that return nonsynchronicity is a measure of corporate transparency. When firm information is timely and accurately disclosed and released, market participants promptly and effectively analyze the information and make similar decisions in their trades. Thus, stock prices move synchronously with the market return, resulting in a low return nonsynchronicity. However, a lack of corporate transparency causes uncertainty on the arrival of information. Less informed investors thus rely more on macroeconomic information and follow the trades from more relatively informed ones (E. C. Chang et al., 2000). To obtain the return nonsynchronicity of each firm, I run the market model as shown in equation (1) of daily returns over the period of study in order to obtain the  $R - Squared$  in each month for the variable definition as shown in equation (2).

$$R_{i,t} = \alpha + \gamma_1 R_{m,t}^{SET} + \varepsilon_t \quad (1)$$

$$NSYNC_i = \ln \left[ \frac{1 - (R - Squared)_i}{R - Squared_i} \right] \quad (2)$$

where  $R_{i,t}$  is a daily individual stock return of firm  $i$  on day  $t$ ,  $R_{m,t}^{SET}$  is a daily SET index market return on day  $t$ , and  $\varepsilon_t$  is a residual term on day  $t$ .  $NSYNC_i$  is the return nonsynchronicity of firm  $i$ .  $R - Squared_i$  is the coefficient of determination of firm  $i$  obtained from the market model shown in equation (1) for a given month.  $\ln$  is natural logarithm.

Second, the monthly standardized residual return is an error term ( $\varepsilon_t$ ) of the market model, which represents as a noise trading activity as it shows news-based return volatility (Aabo et al., 2017; Blitz et al., 2011). Thus, the residual return is driven by firm-specific information rather than noise. Noise traders are considered as uninformed traders, who lack sufficient information to make a trade. The larger the number of noise traders is, the higher the likelihood of herd behavior is (Spyrou, 2013).

Third, the monthly return skewness ( $SKEW_t$ ) represents an asymmetry in firm-specific return variation (Nguyen et al., 2018), which is shown in equation (3) below.<sup>9</sup> Over periods of extreme conditions, information asymmetry is enlarged, boosting the skewness of return. Investors tend to



disregard their own private information and to track an observed decision during extreme periods (Deng et al., 2018).

$$SKEW_t = \frac{T(T-1)^{\frac{3}{2}} \sum_{t=1}^T (R_{i,t} - \bar{R}_i)^3}{(T-1)(T-2) \left( \sum_{t=1}^T (R_{i,t} - \bar{R}_i)^2 \right)^{\frac{3}{2}}} \quad (3)$$

where  $\bar{R}_i$  is an average return of firm  $i$  during a given month, and  $T$  is a number of daily observations in a particular month.

Last, the monthly information discreteness ( $ID_t$ ) presented in equation (4) demonstrates stock illiquidity introduced by Da et al. (2014), who suggest that a continuity in return be associated with a frequency of information disclosure. Less illiquid firms are likely to be large and transparent firms, showing a smaller tendency of herd behavior (Taylor, 2002).

$$ID_M = \text{sign}(\text{Cumulative}_M) \times (\% \text{Negative}_M - \% \text{Positive}_M) \quad (4)$$

where  $\text{sign}(\text{Cumulative}_M)$  is a sign of cumulative raw returns during month  $M$ .  $\% \text{Negative}_M$  ( $\% \text{Positive}_M$ ) is a percentage of negative (positive) return dates during month  $M$ .

#### 4.2. Herd behavior and firm-specific information

One of the most popular aggregate herding detection models is developed by E. C. Chang et al. (2000). Starting from a rational asset pricing model, the model demonstrates that the linear relationship of return dispersion and market return is not sufficient to explain herd behavior, an inclusion of non-linear return would help capture true herd behavior. Thus, herd behavior as shown in equations (5) and (6) is dominant when the rational asset pricing model is violated under two cases. First, a significant and negative coefficient of  $|R_{m,t}|$  shows severe herd behavior. Second, without a significantly negative coefficient of  $|R_{m,t}|$ , a significant and negative (positive) coefficient of  $R_{m,t}^2$  indicates herd behavior (anti-herd behavior).

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (5)$$

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (6)$$

where  $CSAD_t$  is a cross-sectional absolute deviation of returns on day  $t$ ,  $N$  is the number of stocks in a given portfolio, and  $R_{i,t}$  is a daily individual stock return of firm  $i$  on day  $t$ , which is  $100 \times (\ln(P_{i,t}) - \ln(P_{i,t-1}))$ .  $\ln$  is natural logarithm.  $R_{m,t}$  is an equally weighted portfolio return<sup>10</sup> on day  $t$ , and  $\varepsilon_t$  is an error term on day  $t$ .

This paper incorporates the potential effects of four-type of firm-specific return variation into the E. C. Chang et al.'s (2000) herd behavior model as follows.

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_L + \gamma_4 D_H + \gamma_5 D_L |R_{m,t}| + \gamma_6 D_L R_{m,t}^2 + \gamma_7 D_H |R_{m,t}| + \gamma_8 D_H R_{m,t}^2 + \varepsilon_t \quad (7)$$

where  $D_L$  is equal to one when a measure of firm-specific return variation falls below the 25th percentile, and zero otherwise. A dummy variable  $D_H$  is equal to one when a measure of firm-specific return variation falls above the 75th percentile, and zero otherwise. Estimated coefficients of  $\gamma_5$  to  $\gamma_8$  are variables of interest. Either negative and significant  $\gamma_5$  or  $\gamma_6$  demonstrates herd



behavior among the lower 25th percentile stocks, while either negative and significant  $\gamma_7$  or  $\gamma_8$  demonstrates herd behavior among the higher 75th percentile stocks.

An asymmetry of herd behavior between the negative market return period and the remaining period is shown in equation (8). Moreover, I investigated the impact of major financial crises on herd behavior in equation (9).

$$\begin{aligned}
 CSAD_t = & \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_d + \gamma_4 D_d |R_{m,t}| + \gamma_5 D_d R_{m,t}^2 + \gamma_6 D_L + \gamma_7 D_H \\
 & + \gamma_8 D_d D_L + \gamma_9 D_d D_H + \gamma_{10} D_L |R_{m,t}| + \gamma_{11} D_L R_{m,t}^2 + \gamma_{12} D_H |R_{m,t}| \\
 & + \gamma_{13} D_H R_{m,t}^2 + \gamma_{14} D_d D_L |R_{m,t}| + \gamma_{15} D_d D_L R_{m,t}^2 + \gamma_{16} D_d D_H |R_{m,t}| \\
 & + \gamma_{17} D_d D_H R_{m,t}^2 + \varepsilon_t
 \end{aligned} \tag{8}$$

$$\begin{aligned}
 CSAD_t = & \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_c + \gamma_4 D_c |R_{m,t}| + \gamma_5 D_c R_{m,t}^2 + \gamma_6 D_L + \gamma_7 D_H \\
 & + \gamma_8 D_c D_L + \gamma_9 D_c D_H + \gamma_{10} D_L |R_{m,t}| + \gamma_{11} D_L R_{m,t}^2 + \gamma_{12} D_H |R_{m,t}| + \gamma_{13} D_H R_{m,t}^2 + \gamma_{14} D_c D_L |R_{m,t}| \\
 & + \gamma_{15} D_c D_L R_{m,t}^2 + \gamma_{16} D_c D_H |R_{m,t}| + \gamma_{17} D_c D_H R_{m,t}^2 + \varepsilon_t
 \end{aligned} \tag{9}$$

where  $D_d$  is a dummy variable on negative movement dates, which is equal to one during the period of less-than-zero market return, and zero otherwise.  $D_c$  is a dummy variable on financial crisis dates, which is equal to one during the Asian financial crisis (1 July 1997 to 31 December 1998) and the Global financial crisis (1 March 2008 to 31 March 2009), and zero otherwise. Given equations (8) and (9),  $\gamma_{14}$  to  $\gamma_{17}$  are estimated coefficients of interest, which are expected to be significant and negative in order to validate an asymmetry of herd behavior during the negative market return periods and the crisis periods.

The models in this study have overcome two major drawbacks in prior literature. First, the test of asymmetric herd behavior in the work of E. C. Chang et al. (2000) is designed to split the data based on different market conditions, and then run each model separately. This would suffer a sample-splitting problem. Second, Chiang and Zheng (2010) suggest the tests of asymmetric herd behavior and herd behavior during the financial crisis periods by using the dummy variable approach. Putting both *dummyvariable* and  $(1 - \text{dummyvariable})$  in the same equation would cause multicollinearity. In summary, the estimations in this paper alleviate these two problems, subsequently yielding better results.<sup>11</sup>

## 5. Empirical results

Table 1 demonstrates the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily equally weighted market returns ( $R_m$ ). The return dispersion ranges from 0.019% to 10.559% per day over the examined period of study, whereas the market return moves approximately -11.604% to 9.872% per day with a high standard deviation of 1.282% per day signaling a high stock's market volatility in the Stock Exchange of Thailand. Statistically significant augmented Dickey-Fuller (ADF) tests of these two main variables demonstrate an absence of unit root, meaning that the time-series data are consistent with the stationary assumption and fit for model testing shown in further steps. Although an autocorrelation is relatively low among long lag periods, it still presents a large magnitude of serial correlation, especially for the CSAD. Thus, the heteroscedasticity and autocorrelation consistent standard error developed by Newey and West (1987) is employed throughout the study.

### 5.1. Aggregate market herding

In this study, I extend the E. C. Chang et al.'s (2000) herding detection model by incorporating measures of firm-specific information under several scenarios. Interaction terms between firm-specific return variation and market return variables are estimated coefficients of interest.

**Table 1. Descriptive statistics**

Variable	Average (%)	Min (%)	Max (%)	S.D. (%)	ADF	Serial correlation at lag				
						1	2	3	5	20
CSAD	1.950	0.019	10.559	0.915	-5.709***	0.834	0.798	0.770	0.730	0.673
$R_m$	-0.001	-11.604	9.872	1.282	-16.046***	0.217	0.100	0.081	0.027	0.011

This table reports descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily equally weighted market portfolio returns ( $R_m$ ). ADF is the augmented Dickey-Fuller test. \*\*\* indicates statistical significance at the 1% level.

A negative coefficient of  $|R_{m,t}|$  suggests severe herd behavior, whereas a positive coefficient of  $|R_{m,t}|$  with a negative coefficient of  $R_{m,t}^2$  indicates a slope reduction in the aggregate market herding. On the other hand, a positive coefficient of  $|R_{m,t}|$  with a positive coefficient of  $R_{m,t}^2$  is a sign of anti-herd behavior, implying that investors rely on their own trading decision rather than market consensus.

Column (1) of Table 2 presents the aggregate market herd behavior over the entire sample. In general, the herd behavior based on the model suggested by E. C. Chang et al.'s (2000) is evident in the Thai stock market, showing the significantly positive linear term ( $|R_{m,t}|$ ) and significantly negative non-linear term ( $R_{m,t}^2$ ) with the 35.3% adjusted R-squared value. This means that a return dispersion increases at a decreasing rate, given an increase in the absolute value of market return. A reduction of return dispersion denotes a violation of a rational asset pricing model signifying pure herd behavior in Thailand (Chang & Lin, 2015; Chen, 2013; Chiang & Zheng, 2010).

Table 2. Herd behavior and firm-specific information					
	(1)	(2)	(3)	(4)	(5)
	Chang et al.	Nonsync	Resid	Skew	ID
Intercept	1.369*** (74.85)	1.545*** (48.49)	1.558*** (83.80)	1.647*** (78.83)	1.576*** (55.66)
$ R_{m,t} $	0.790*** (20.26)	0.524*** (8.78)	0.416*** (15.77)	0.594*** (21.43)	0.683*** (13.31)
$R_{m,t}^2$	-0.050*** (-4.97)	-0.006 (-0.36)	-0.025*** (-4.43)	-0.055*** (-12.00)	-0.052*** (-4.24)
$D_L$		-0.032 (-0.85)	-0.351*** (-17.24)	-0.232*** (-8.60)	-0.086*** (-2.74)
$D_H$		-0.307*** (-7.00)	0.338*** (8.97)	-0.244*** (-8.49)	-0.288*** (-8.75)
$D_L R_{m,t} $		-0.003 (-0.04)	-0.075** (-2.32)	0.060 (1.26)	-0.082 (-1.25)
$D_LR_{m,t}^2$		-0.023 (-1.14)	0.044*** (7.37)	0.050*** (5.80)	0.038** (2.33)
$D_H R_{m,t} $		0.502*** (4.78)	0.414*** (6.12)	0.154*** (2.74)	0.123 (1.57)
$D_HR_{m,t}^2$		0.051 (1.53)	-0.029* (-1.67)	0.079*** (5.00)	0.061** (2.10)
Adj.R <sup>2</sup>	0.353	0.446	0.565	0.422	0.384

This table reports the estimated results of the aggregate market herd behavior by employing the E. C. Chang et al. (2000) model with firm-specific information. The regression model is  $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2R_{m,t}^2 + \gamma_3D_L + \gamma_4D_H + \gamma_5D_L|R_{m,t}| + \gamma_6D_LR_{m,t}^2 + \gamma_7D_H|R_{m,t}| + \gamma_8D_HR_{m,t}^2 + \epsilon_t$ , where  $CSAD_t$  is the cross-sectional absolute deviation of return at time  $t$ .  $R_{m,t}$  is an equally weighted portfolio return at time  $t$ .  $D_L$  is equal to one if a particular firm-specific information falls below the 25th percentile, and zero otherwise.  $D_H$  is equal to one if a particular firm-specific information falls above the 75th percentile, and zero otherwise. Four measures of firm-specific information are return nonsynchronicity (Nonsync), return residual (Resid), return skewness (Skew), and information discreteness (ID). Return nonsynchronicity ( $NSYNC_t$ ) is measured by the logistic transformation of the coefficient of determination of the market model, which is used as a proxy of corporate transparency. Residual return is an error term of the market model, which represents as a noise trading activity. Return skewness represents an asymmetry in firm-specific return variation. Information discreteness shows a continuity in return be associated to a frequency of information disclosure, referred to stock illiquidity. The calculations of each measure are shown in Section 4 Methodology. t-statistics are shown in parentheses, which is calculated by using Newey and West (1987)'s heteroscedasticity and autocorrelation consistent standard errors. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Columns (2) to (5) of Table 2 show the associations between herd behavior and firm-specific information. In general, an inclusion of firm-specific information improves the fitness of the models, generating 38.4% to 56.5% adjusted R-squared values. Preliminarily, the below 25th percentile and the above 75th percentile dummy variables of each firm-specific information measure are negative and statistically significant in most cases, meaning that extreme values of firm-specific return variations are associated to return dispersion. However, I focused on interaction terms, which reflect an effect of each measure of firm-specific information on aggregate herd behavior. As shown in Column (3), the below 25th percentile of residual return shows severe herd behavior as the coefficient of  $D_L|R_{m,t}|$  is significantly negative. Because a high (low) value of residual return shows a high (low) tendency of noise trading (Aabo et al., 2017), the results suggest that herd behavior is mainly driven from informed traders (comparatively less in uninformed traders)<sup>12</sup> is likely to be unintentional herd.<sup>13</sup> However, due to the significantly positive  $D_L R_{m,t}^2$ , the mimicking trades decline, given an increase in the absolute market return. Conversely, the above 75th percentile of residual return demonstrates a relatively weaker herd behavior than the bottom percentile because it shows the significantly positive in the linear interaction term ( $D_H|R_{m,t}|$ ) and significantly negative in the nonlinear interaction term ( $D_H R_{m,t}^2$ ). This implies that noise traders mainly cause intentional herding. Unfortunately, I do not find herd behavior in the rest of firm-specific information measures. Nevertheless, it is interesting to note that both high and low percentiles of return skewness (Column 4) and information discreteness (Column 5) demonstrate possible anti-herding behavior based on the positive coefficients of  $D_L R_{m,t}^2$  and  $D_H R_{m,t}^2$ . The results are in line with the findings of Hwang and Salmon (2004), who state that market stress as an extreme market condition is associated with herd behavior and Messis and Zapranis (2014) discover the relationship between systematic skewness and herd behavior. As return skewness is a representative of information asymmetry (Deng et al., 2018), herd behavior is definitely affected, especially during bull and bear markets. Thus, return skewness is a condition of herd behavior. Weak evidence on the information discreteness is found along with the findings of Taylor (2002) and Galariotisa et al. (2016), who show that stock liquidity (measured by information discreteness) influences herd behavior. Unfortunately, herd behavior is not present in the return nonsynchronicity as shown in Column (2). In summary, the aggregate herd behavior exists in the Thai equity market, especially for the return residual firm-specific information.

## 5.2. Asymmetric herd behavior

Seminal papers (E. C. Chang et al., 2000; Chiang & Zheng, 2010) suggest that herd behavior is asymmetric between positive and negative return periods. Table 3 reports the associations between firm-specific information and herd behavior by incorporating an impact of market conditions. A negative return period is defined as a situation that an equally weighted market return is below zero. Overall, the results during negative return periods are stronger than previous results and the R-squared values remain large. The estimated coefficients of  $D_d D_L|R_{m,t}|$ ,  $D_d D_L R_{m,t}^2$ ,  $D_d D_H|R_{m,t}|$ , and  $D_d D_H R_{m,t}^2$  are of main interest. The return nonsynchronicity as shown in Column (2) shows severe herd behavior over both extreme percentiles; however, those of residual returns in Column (3) and return skewness in Column (4) demonstrate herd behavior only in the 25th percentile and the 75th percentile, respectively.

The return nonsynchronicity and return skewness suggest severe herd behavior during negative return periods. Both the uppermost and lowermost percentiles of return nonsynchronicity demonstrate strong herd behavior, but a degree of imitating trades reduces when an absolute market return increases. In general, the evidence on return nonsynchronicity is much stronger than in the previous section. As the return nonsynchronicity is a proxy of corporate transparency, transparent firms disclose effectively comparable information to investors, which is a preferable circumstance for unintentional herding (Choi & Skiba, 2015). Oppositely, the number of less informative investors is large in opaque (less transparent) firms, subsequently attracting intentional herding (Gelos & Wei, 2005).

Table 3. Herd behavior during the negative market condition and firm-specific information

	(1)	(2)	(3)	(4)	(5)
	Chang et al.	Nonsync	Resid	Skew	ID
Intercept	1.316*** (49.37)	1.618*** (45.46)	1.555*** (66.79)	1.610*** (61.15)	1.575*** (35.28)
$ R_{m,t} $	0.850*** (13.26)	0.352*** (5.17)	0.483*** (14.49)	0.640*** (16.93)	0.659*** (7.15)
$R_{m,t}^2$	-0.058*** (-2.89)	0.036 (1.58)	-0.043*** (-5.18)	-0.065*** (-8.69)	-0.046* (-1.69)
$D_d$	0.114*** (3.05)	-0.164*** (-2.98)	-0.014 (-0.39)	0.086** (2.17)	0.015 (0.27)
$D_d R_{m,t} $	-0.119 (-1.47)	0.381*** (3.97)	-0.110** (-2.15)	-0.112** (-2.05)	0.025 (0.23)
$D_dR_{m,t}^2$	0.014 (0.63)	-0.084*** (-3.21)	0.028** (2.46)	0.020** (2.10)	-0.010 (-0.35)
$D_L$		-0.177*** (-4.30)	-0.344*** (-13.41)	-0.198*** (-5.75)	-0.080* (-1.85)
$D_H$		-0.394*** (-9.98)	0.287*** (5.16)	-0.300*** (-8.49)	-0.359*** (-7.50)
$D_dD_L$		0.248*** (3.85)	0.009 (0.25)	-0.086 (-1.55)	-0.036 (-0.58)
$D_dD_H$		0.306*** (4.72)	0.129* (1.71)	0.169*** (3.09)	0.155** (2.32)
$D_L R_{m,t} $		0.403*** (5.02)	-0.154*** (-3.63)	-0.026 (-0.34)	-0.092 (-0.87)
$D_LR_{m,t}^2$		-0.114*** (-3.21)	0.069*** (2.46)	0.046* (1.69)	0.012 (0.27)

(Continued)

Table 3. (Continued)

(1)	(2)	(3)	(4)	(5)
Chang et al.	Nonsync	Resid	Skew	ID
$D_H   R_{m,t}$	(-4.84) 0.538***	(6.25) 0.355***	(1.67) 0.265***	(0.35) 0.249**
$D_H R_{m,t}^2$	(6.77) 0.050***	(3.23) -0.007	(3.94) 0.069***	(2.19) 0.049
$D_d D_L   R_{m,t}$	(2.92) -0.719***	(-0.23) 0.121*	(4.24) 0.202**	(1.29) 0.060
$D_d D_L R_{m,t}^2$	(-6.39) 0.154***	(1.94) -0.036***	(1.99) -0.010	(0.46) 0.028
$D_H D_H   R_{m,t}$	(5.36) -0.410***	(-2.69) 0.084	(-0.35) -0.334***	(0.78) -0.203
$D_d D_H R_{m,t}^2$	(-2.94) 0.122***	(0.61) -0.033	(-3.12) 0.050	(-1.13) -0.016
Adj. R <sup>2</sup>	(2.62) 0.461	(-0.89) 0.567	(1.36) 0.426	(-0.20) 0.388

This table reports the estimated results of the aggregate market herd behavior during negative market periods by employing the E. C. Chang et al. (2000) model with firm-specific information. The regression is

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_d |R_{m,t}| + \gamma_4 D_d |R_{m,t}| + \gamma_5 D_d R_{m,t}^2 + \gamma_6 D_L + \gamma_7 D_H + \gamma_8 D_d D_L + \gamma_9 D_d D_H + \gamma_{10} D_L |R_{m,t}| + \gamma_{11} D_L R_{m,t}^2 + \gamma_{12} D_H |R_{m,t}| + \gamma_{13} D_H R_{m,t}^2 + \gamma_{14} D_d D_L |R_{m,t}| + \gamma_{15} D_d D_L R_{m,t}^2 + \gamma_{16} D_d D_H |R_{m,t}| + \gamma_{17} D_d D_H R_{m,t}^2 + \epsilon_t$$

where CSAD<sub>t</sub> is the cross-sectional absolute deviation of return at time t. R<sub>m,t</sub> is an equally weighted portfolio return at time t. D<sub>d</sub> is a dummy variable for the down market date. It is equal to one on the negative market return date, and zero otherwise. D<sub>L</sub> is equal to one if a particular firm-specific information falls below the 25th percentile, and zero otherwise. D<sub>H</sub> is equal to one if a particular firm-specific information falls above the 75th percentile, and zero otherwise. Four measures of firm-specific information are return nonsynchronicity (Nonsync), return residual (Resid), return skewness (Skew), and information discreteness (ID). Return nonsynchronicity (MSYNG<sub>t</sub>) is measured by the logistic transformation of the coefficient of determination of the market model, which is used as a proxy of corporate transparency. Residual return is an error term of the market model, which represents as a noise trading activity. Return skewness represents an asymmetry in firm-specific return variation. Information discreteness shows a continuity in return be associated to a frequency of information disclosure, referred to stock illiquidity. The calculations of each measure are shown in Section 4 Methodology. t-statistics are shown in parentheses, which is calculated by using Newey and West (1987)'s heteroscedasticity and autocorrelation consistent standard errors. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The above 75th percentile of return skewness also indicates severe herd behavior without a decreasing trend, supporting that an information asymmetry facilitates a likelihood of aggregate market herd behavior, especially during a downward movement (Zhou & Anderson, 2013). Moreover, the below 25th percentile of return residual presents herd behavior, supporting that informed traders mainly induce unintentional herd behavior. The estimated coefficients of interest of the information discreteness model in Column (5) are not significant, but still negative, suggesting a possibility of aggregate herd behavior. In summary, herd behavior with firm-specific return variations is stronger during the negative market condition.

### 5.3. Herd behavior during financial crisis

Seminal studies (Christie & Huang, 1995; Chiang & Zheng, 2010; Zhou & Anderson, 2013) suggest that herd behavior is more prevalent during financial turbulent periods. Thus, the effects of the Asian financial crisis (1 July 1997 to 31 December 1998) and the global financial crisis (1 March 2008 to 31 March 2009) are included and the estimated results are presented in Table 4. Overall, the models are the best fit when compared to previous models as the adjusted R-squared values range from 56.0% to 71.6%. In this model, all firm-specific information measures generally support herd behavior. It is interesting to note that the coefficients of  $D_c D_L R_{m,t}^2$  and  $D_c D_H R_{m,t}^2$  for return skewness in Column (4) are not significant, but still negative. The significantly negative  $D_c D_L |R_{m,t}|$  of residual return in Column (3) denotes severe herd behavior during financial crises among the group of the lowest 25th percentile. This confirms an important role of informed traders on unintentional herd behavior as shown in Table 3, while the noise traders play no role in the group of the 75th percentile. The residual return is the only firm-specific information that affects herd behavior in all cases as presented in Table 2–4. This confirms evidence on the impact of idiosyncratic volatility on herd behavior in prior literature (Vo and Phan, 2019).

The above 75th percentile of nonsynchronicity as presented in Column (2) of Table 4 signifies the aggregate market herd behavior related to corporate transparency. It is expected as herd behavior is prevalent when investors do not possess sufficient information for opaque (less transparent) firms. The result is in line with the findings of Wang and Huang (2018). During the financial turbulent periods, the above 75th percentile of information discreteness demonstrates that herd behavior is stronger than the below 25th percentile, showing that the herd behavior is more prevalent among low liquid stocks. The evidence is supported by the findings of Taylor (2002), documenting that stock returns are more clustered among illiquid stock. Moreover, low liquid assets are mostly small stocks, showing a large information asymmetry and an occurrence of intentional herding. However, due to a less significant information discreteness of the bottom 25th percentile, it shows that high liquid (less information discreteness) assets possess the same set of information; thus, the decisions are largely similar, showing unintentional herding.

### 6. Conclusion

Studies of firm-specific information on asset pricing have gained attention in literature, but it is not the case for the study of herd behavior. One of the most influential herd detection models is developed by E. C. Chang et al. (2000), which is derived from the asset pricing model. In this regard, firm-specific information should be included in the herd behavior model in the same manner. However, the study of the impact of firm-specific information on herd behavior is still limited. This paper aims to fill the gap in the literature.

I employ four popular measures of firm-specific information, including return nonsynchronicity, return residual, return skewness, and information discreteness, to investigate impacts on herd behavior in the Stock Exchange of Thailand—an emerging market is easier to find herd behavior than advanced equity markets. Overall, the herd behavior is primarily prevalent in the Thai stock market, yet proving to be even stronger during the negative market return and the financial turbulent periods. This confirms an asymmetry in the aggregate herd behavior found in prior literature. All firm-specific information measures play a critical role in determining the level of herd



**Table 4. Herd behavior during crisis periods and firm-specific information**

	(1)	(2)	(3)	(4)	(5)
	<b>Crisis</b>	<b>Nonsync</b>	<b>Resid</b>	<b>Skew</b>	<b>ID</b>
<i>Intercept</i>	1.361*** (82.00)	1.527*** (60.37)	1.525*** (83.47)	1.601*** (91.73)	1.539*** (88.56)
$ R_{m,t} $	0.648*** (17.78)	0.521*** (12.02)	0.409*** (15.35)	0.513*** (21.99)	0.582*** (23.28)
$R_{m,t}^2$	-0.044*** (-4.45)	-0.020 (-1.57)	-0.023*** (-4.00)	-0.044*** (-10.04)	-0.050*** (-10.49)
$D_c$	0.869*** (8.61)	1.119*** (4.75)	1.422*** (10.17)	2.022*** (10.50)	1.571*** (9.84)
$D_c R_{m,t} $	0.537*** (5.31)	0.270 (1.28)	0.482* (1.76)	0.141 (0.66)	0.267* (1.93)
$D_cR_{m,t}^2$	-0.016 (-0.76)	0.008 (0.18)	-0.159 (-0.70)	0.033 (0.59)	0.037** (2.35)
$D_L$		-0.006 (-0.19)	-0.325*** (-17.06)	-0.234*** (-11.42)	-0.083*** (-3.58)
$D_H$		-0.215*** (-6.52)	0.287*** (8.98)	-0.176*** (-7.26)	-0.240*** (-10.27)
$D_cD_L$		-0.607*** (-2.96)	-1.233*** (-9.58)	-1.068*** (-5.20)	-0.630*** (-3.71)
$D_cD_H$		0.009 (0.04)	-0.151* (-1.85)	-0.624*** (-3.81)	-0.858*** (-5.09)
$D_L R_{m,t} $		-0.056 (-0.92)	-0.003 (-0.09)	-0.044 (-1.25)	-0.156*** (-3.18)
$D_LR_{m,t}^2$		-0.006	0.036***	0.049***	0.046***

(Continued)

Table 4. (Continued)

	(1) Crisis	(2) Nonsync	(3) Resid	(4) Skew	(5) ID
$D_H   R_{m,t}$		(-0.37) -0.076	(6.05) 0.238***	(6.42) 0.134**	(3.38) 0.108*
$D_H R_{m,t}^2$		(-0.80) 0.216***	(4.03) -0.027*	(2.01) 0.054*	(1.81) 0.068**
$D_c D_L   R_{m,t}$		(4.39) 0.238	(-1.74) -0.487***	(1.68) 0.400*	(2.46) 0.258
$D_c D_L R_{m,t}^2$		(1.13) -0.028	(-2.95) 0.062	(1.86) -0.088	(1.43) -0.070**
$D_c D_H   R_{m,t}$		(-0.68) 0.409**	(1.06) -0.291	(-1.58) 0.254	(-2.51) 0.617**
$D_c D_H R_{m,t}^2$		(1.97) -0.221***	(-1.11) 0.181	(1.20) -0.077	(2.55) -0.212***
Adj. $R^2$	0.560	(-3.95) 0.598	(0.80) 0.716	(-1.21) 0.620	(-3.36) 0.603

This table reports the estimated results of the aggregate market herd behavior during financial crisis periods by employing the E. C. Chang et al. (2000) model with firm-specific information. The regression is  $CSAD_{i,t} = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 D_c + \gamma_4 D_c |R_{m,t}| + \gamma_5 D_c R_{m,t}^2 + \gamma_6 D_L + \gamma_7 D_H + \gamma_8 D_c D_L + \gamma_9 D_c D_H + \gamma_{10} D_L |R_{m,t}| + \gamma_{11} D_L R_{m,t}^2 + \gamma_{12} D_H |R_{m,t}| + \gamma_{13} D_H R_{m,t}^2 + \gamma_{14} D_c D_L |R_{m,t}| + \gamma_{15} D_c D_L R_{m,t}^2 + \gamma_{16} D_c D_H |R_{m,t}| + \gamma_{17} D_c D_H R_{m,t}^2 + \epsilon_t$ , where  $CSAD_{i,t}$  is the cross-sectional absolute deviation of return at time  $t$ ,  $R_{m,t}$  is an equally weighted portfolio return at time  $t$ ,  $D_c$  is a dummy variable on the financial crisis date. It is equal to one during the periods of the Asian financial crisis (1 July 1997 to 31 December 1998) and the Global financial crisis (1 March 2008 to 31 March 2009), and zero otherwise.  $D_L$  is equal to one if a particular firm-specific information falls below the 25th percentile, and zero otherwise.  $D_H$  is equal to one if a particular firm-specific information falls above the 75th percentile, and zero otherwise. Four measures of firm-specific information are return nonsynchronicity (Nonsync), return residual (Resid), return skewness (Skew), and information discreteness (ID). Return nonsynchronicity (NSYNC) is measured by the logistic transformation of the coefficient of determination of the market model, which is used as a proxy of corporate transparency. Residual return is an error term of the market model, which represents as a noise trading activity. Return skewness represents an asymmetry in firm-specific return variation. Information discreteness shows a continuity in return be associated to a frequency of information disclosure, referred to stock illiquidity. The calculations of each measure are shown in Section 4 Methodology. t-statistics are shown in parentheses, which is calculated by using Newey and West (1987)'s heteroscedasticity and autocorrelation consistent standard errors. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

behavior. On a more specific note, the residual return is statistically significant in all cases, showing an important role of noise trading on the aggregate herd behavior. The results are linked to two types of herd behavior, that is, intentional herding and unintentional herding. As return nonsynchronicity, return residual, return skewness, and information discreteness are proxies of corporate transparency, noise trading, asymmetric information, and illiquidity, respectively. I conclude that intentional herd is driven by high return nonsynchronicity, high return residual, high skewness, and low liquidity.

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#### Notes

1. Easley et al. (1996) and Easley et al. (1997) present a new powerful measure of informed trading (so called as the probability of informed trading: PIN), measured by the total number of traders and the order imbalance. The model relies on the fact that the order imbalance is driven by informed trading.
2. Herding involves in human decision-making for both sophisticated and naive people, even in economic and financial decisions. Traditionally, studies of herd behavior focus on two aspects, that is, return and volatility. Some argue that herd behavior is bad for economy, because it accelerates volatility in the market. People imitate activities by others and ignore their own private information and belief. For example, Bikhchandani and Sharma (2000) point out that it is necessary to differentiate two types of herd behavior, that is, intentional (true) and unintentional (spurious). Intentional herd behavior is blamed to be a cause of uncertainty in stock market because of information cascade, thus making the stock market more volatile. Unintentional herd behavior might occur to reflect public information, hence pushing stock prices to be informationally efficient.
3. There are 28 sectors from eight industries in the Stock Exchange of Thailand. As of 1 January 2020, there are 13 sectors in the SET50 index that the constituent stocks in the index are revised every six months.
4. Institutional investors are momentum traders (Nofsinger & Sias, 1999) and considered as informed traders. Retail investors are contrarians and considered as uninformed traders (Kaniel et al., 2008).
5. The early review of literature was written by Hirshleifer and Hong Teoh (2003).

6. For example, Economou et al. (2011) in Portugal, Italy, Spain and Greece and Henker et al. (2006) in Australia.
7. This is suggested by Blitz et al. (2011).
8. See Morck et al. (2000) and Chen et al. (2007).
9. This is in line with the weekly skewness variable employed in the study of Kim et al. (2011) and An and Zhang (2013).
10. An equally weighted portfolio return is preferred to a valued weighted portfolio return because individual stocks equally contribute to herd behavior at the aggregate level, regardless of firm's size. This is important for an under-developed equity market, which the stock market index is overweighed by a small number of large stocks. Thus, the valued weighted return misleads an estimation.
11. The methodology employed in this study is consistent with the suggestions of Wanidwaranan and Padungsaksawasdi (2020), who study herd behavior when return jumps occurs.
12. I infer that the below 25th percentile of return residual shows a less role of noise traders on herd behavior. Thus, the behavior occurs because of trading pressure of informed traders.
13. Bikhchandani and Sharma (2000) define the unintentional herding as a spurious herd-like phenomenon. A similar trading decision is a result of the same comparable information. Due to uninformative decision-making, noise traders are anticipated to be a key contributor of intentional herding. A deliberately mimicking judgement without knowing an underlying reason is intentional herding.

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