Journal of Behavioral and Experimental Finance 29 (2021) 100466

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

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

Full length article

Static and regime-dependent herding behavior: An emerging market case study

Abdollah Ah Mand [a], Imtiaz Sifat [b,*]

[a] Department of Economics & Finance, Sunway University Business School, Sunway University, Bandar Sunway, Petaling Jaya, 47500, Selangor, Malaysia
[b] Department of Accounting & Finance, Monash University Malaysia, Jalan L, Subang Jaya, 47500, Selangor, Malaysia

A R T I C L E I N F O

Article history:
Received 1 November 2020
Received in revised form 10 January 2021
Accepted 18 January 2021
Available online 20 January 2021

JEL classification:
Codes
C63
D84
G1
G2
G15
F4

Keywords:
Herd behavior
Herding
Behavioral finance
Malaysia
Bursa Malaysia

A B S T R A C T

We contribute to behavioral finance literature by demonstrating the relative superiority of a dynamic regime-sensitive approach in unraveling herding phenomenon. Employing daily data in Bursa Malaysia from 1995 to 2016, we first apply two orthodox techniques: cross-sectional standard deviation of returns (CSSD) model of Christie and Huang (2005) and the cross-sectional absolute dispersion (CSAD) model of Chang et al. (2000). The ensuing results appear inconsistent, with only one model capturing herding. In contrast, the dynamic approach with a two-state Markov Switching model reveals that herding is a heavily regime-dependent and non-linear phenomenon. A deeper dive via sectoral decompositions shows that the financial sector and large- and mid-capitalization segments are more herding-prone.

1. Introduction

Stock markets have long been considered a mirror of the underlying economy's health. Thus, a stable stock market is usually an indication of investors' sanguine bet on the economy's prospects. Despite this theoretical tether to the real economy, research shows that investment decisions in the markets are guided by various non-fundamental and non-rational considerations. In fact, a sprawling body of literature connected to this has emerged over the past two decades, dwelling on the behavioral anomalies of investment antecedents in stock markets. A major such anomaly is investors' propensity to ape other investors' choices instead of independent, private, or atomistic trading decisions. This phenomenon is formally known as herding behavior. Earliest motivation for works on herding behavior can be traced to Keynes (1930), who remarked on the allure of indecision and imitating the crowd. He attributed such behavior to the notion that the crowd knows better than the individual, before famously remarking: *"…it is better to fail conventionally than to succeed unconventionally"*. Though Keynes was not referring to the stock markets *per se*, his points have strong implications for the financial markets, where herding behavior has been shown to fuel speculation, leading to bubbles that eventually burst.

On the theoretical front, if herding is ubiquitous, it invites a reexamination of explanations tied to market efficiency. Research in this area so far is widely dominated by the efficient market hypothesis (EMH) (Fama et al., 1969). EMH can be categorized into three basic forms: Weak-form EMH, which claims that prices on financial assets reflect all past publicly available information; semi-strong EMH implies that all public information is calculated into a stock's current share price, meaning neither fundamental nor technical analysis can be used to achieve superior gains. Lastly, strong-form EMH is the strongest version of market efficiency and it states that all information in a market, whether public or private, is accounted for in a stock's price. EMH relies on the rationality of investors using market information in making decisions. In practice, substantial evidence has been documented suggesting irrationality of investors' decision making.

* Corresponding author.
E-mail addresses: abdollaha@sunway.edu.my (A. Ah Mand), imtiaz@sifat.asia, imtiaz.sifat@monash.edu (I. Sifat).

https://doi.org/10.1016/j.jbef.2021.100466
2214-6350/

Moreover, investors sometimes disregard private information in their decisions. Regarding this, Kahneman and Tversky (1979) show that market price does not fully represent the information and there are missing elements in the reflection of market price, which could be the behavioral perspectives of investors. Behavioral elements have been studied by scholars and recent findings support the prior premises regarding irrationality (Chen et al., 2003; Demirer and Kutan, 2006). Taken together, these results hint at the failure and inadequacy of traditional finance theories to capture market pricing mechanisms.

Considering that investment behavior comprises investors who are considered to be irrational, the theory of behavioral finance has emerged as an alternative to the orthodox frameworks for understanding investment behavior in the stock market. Another related theory, the heuristic theory, also has been proposed; it captures other behavioral perspectives of investors: overconfidence in decision making. Overconfidence highlights the degree of people overestimating their performance on cognitive tasks. This phenomenon has been documented among individuals with low cognitive ability as well as in high-achieving geographical regions (Ngoc, 2014; Stankov and Lee, 2014). The premise and findings of these theories help lay the groundwork for understanding herding behavior where investors blindly mimic the behavior of others.

Undergirded by the theoretical developments outlined above, empirical research attention on herding behavior has surged in recent times, driven by several factors. Firstly, a significant chunk of literature appears to support that investors indeed mimic the actions of other investors—a finding with important ramifications for financial markets because herding indicates that investors may be ignoring their private information and, in the process, driving prices away from their fundamental values. Even though such behavior among investors can be driven by rational or irrational motives, it can lead to market stress by pushing asset prices away from their fair values as supported by the researchers; hence, driving up market volatility (Balcilar et al., 2013). The second motivation is related to the combined growth of sophistication and technological access. Case in point: due to proliferation of web-based trading platforms, even small-capital retail investors are able to participate in the markets. Though this increased participation can be thought of as a welcome sign for improvement of liquidity, research shows that smaller investors often contribute to adverse market phenomena such as noise trading, transitory volatility, and irrational mania (e.g., euphoria or panic) (Nassir, 2002; Odean, 1998). These effects are usually considered as results of lack of tools and/or ability to conduct due diligence related to investment analysis or risk management. While a significant number of small investors choose to invest in the markets indirectly via intermediaries (e.g., mutual funds), those intent on active participation value discretionary execution of individual trades or investment decisions. Aside from the fact that the investment needs and goals of this group differs from those of large/institutional investors, enough evidence has accumulated thus far suggesting that smaller investors try to copy the trades of bigger investors. In these scenarios, the retail investors uncritically view the trading decisions of bigger investors as more informed or favorable to self-initiated trades. Thirdly, herding can be a by-product of institutional or foreign investors' need for diversification. Under this rationale, a sub-optimal trading strategy is executed by pursuing similar trades intent on capitalizing on negatively correlated securities to manage broader portfolio risks. This phenomenon is getting more traction lately as global portfolio flows rise to emerging and frontier markets (Economou et al., 2015).

As evidence of herding in finance literature mounts, it is becoming clear that herding in markets is a global phenomenon. In particular, scholars are paying more attention to emerging and frontier markets recently as global portfolio traffic finds palatable the developing economies' markets due to – inter alia – deteriorating yields in traditional financial asset classes. Moreover, the herding phenomena in emerging markets merit closer scrutiny since they differ from established financial centers by virtue of being in budding stages of financial development, lower liquidity and capitalization, imperfect and non-smooth information flow, and idiosyncratic institutional features. These factors motivate us to examine herding behavior in an emerging market that is growing more in importance in the global stage as a capital destination: Malaysia.

Not unlike many emerging markets around the world, the topic of herding behavior in Malaysia has been addressed sporadically by researchers. The nature of such studies has been conducted in a fragmented manner as well. One of the first such studies by Kaminsky and Schmukler (1999) attributed the late 1990s' ASEAN market crashes to herding behavior for the Malaysian market. Lately, Wong and Kok (2009) rely on the CSSD approach to test herding in Malaysia's equity market and find no conclusive evidence of herding. Around the same time, the existence of herding behavior among foreign investors in Bursa Malaysia was confirmed by Duasa and Kassim (2008) who examine foreign portfolio flows to/from Malaysia using error correction techniques. Operating on a country governance framework, Nasarudin et al.'s (2017) 60-country panel study using the CSAD method lists Malaysia among the group of countries where herding behavior exists. All in all, a comprehensive investigation of herding phenomenon in this important emerging market remains unaddressed. We attend to this gap in this paper by pursuing three objectives. First, we employ classical tests of herding phenomenon as per the cross-sectional standard deviation of returns (CSSD) model developed by Christie and Huang and the cross-sectional absolute dispersion (CSAD) model developed by Chang, Cheng and Khorana (CCK). We observe conflicting results from these two approaches, consistent with the methodological criticisms of these techniques as noted by Hwang and Salmon (2004). We then try to improve upon the CH and CCK models by employing a dynamic approach to capture herding. In particular, we note that several recent scholarly works featured experimentation with time-varying coefficients and quantile regression. Along these lines, we make use of a Markov-Switching approach. To this effect, we formulate a two-regime Markov-Switching herding model where the CSAD of Market (Sector) returns can incur a bullish or bearish regime. Lastly, we supplement the broad market results by investigating herding phenomena across major industries, finance, manufacturing, Shariah-compliant and Shariah-non-compliant segments. By pursuing these three objectives, we contribute to empirical finance literature in the following ways. First, our findings constitute the most comprehensive market-wide evidence of (or against) herding behavior in Malaysia. Second, on methodological count, our results reinforce the drawbacks of relying on the traditional CSAD and CSSD based measures of herding. Moreover, we improve upon the static metrics by incorporating a regime-switching model to capture the time-variant attributes of herding. Third, our sectoral disaggregation of herding, along with a market-cap based portfolio approach, provides a richer insight into nuances in herding behavior for emerging market literature. We posit that the higher utility of our approach compared to the existing models is that by allowing parameters of return dispersion vary across the sampling window, we are able to discriminate between the existence and magnitude of herding in bullish and bearish market scenarios, while being able to capture non-linearities due to reliance on second moment information.

The rest of this paper is structured as follows. In Section 2, we review the relevant literature about herding in financial markets, followed by a description of our adopted estimation techniques in Section 3. Section 4 presents our findings along with analyses. Section 5 concludes the paper by recapping the main findings and suggests potential avenues for future research.

2. Literature review

In this section, we synthesize the present state of knowledge regarding herding behavior according to themes prevalent in classical and behavioral finance streams, ending with a brief discussion that contextualizes the literature for our Malaysia-centric investigation.

2.1. Rationality vs. irrationality

Investors' decision to commit to a trading position is ideally expected to be based on individual risk preferences, investment horizons, and expected payoffs. All of these rely on an assumption of rational self-interest maximization. Many studies on investment decisions pursue the rationality of investors and accept the assumption that individuals have rational behavior in their decision makings. These approaches presuppose that people are profit maximizers in their decision of choices. The classical theory of market efficiency builds upon this strand of assumptions, before being challenged by works in behavioral economics and finance in general and prospect theory in particular. In this new stream, researchers attempted to explain the reasoning patterns of investors, with the emotional processes involved and the degree to which investors emphasize the decision-making process. These facts were pointed out by Kahneman and Tversky (1979) who showed that normal decision-making behavior in humans is not consistent with profit maximization motives. Emotion and psychology of the person play a large role (Dang and Lin, 2016). The evolution of behavioral finance models also contributed to investigation of herding behavior, which, by definition, is an anomaly induced by investors' decision-making process. Though tested extensively using various approaches and in different empirical settings, the findings in this field are largely inconclusive. The propensity to herd is demonstrated not merely among market participants but also among professional forecasters (Rülke, 2013). As Devenow and Welch note, three important themes (models) emerge from studies discussed on rational herding behavior in financial markets. which are briefly explained as following; *(i)* Payoff externalities models of herding. Due to an agent's payoff, other agents will adopt the same action to increase their own payoff. *(ii)* Principal–agent models of herding. These types of herding refer to the action of managers in order to protect or gain reputation when the distribution of information is imperfect in the market by "hiding" or "riding" in herds to demonstrate the quality of their work; *(iii)* Cascade models of herding occurs when agents make conclusion from the action of other agents and decide to ignore their own information and follow other's actions (Devenow and Welch, 1996). It is worth mentioning that the application of these themes of rational herding behavior are different in various circumstances. For instance, the rational model of principal–agent models has been investigated by some financial researchers. Their model concerns about herding among managers and concluded reputational concerns are influencing herding among managers. Moreover, correlated predicted errors are also influencing the rational herding behavior of managers. On the other hand, irrational herding behavior may be the result of irrational investor or investor psychology. As an illustration, social gatherings may affect the investors and encourage them to ignore their information and mimic other investors' actions during market uncertainties.

2.2. Seminal works and extensions

A seminal work on the field is for the US market by Christie and Huang (1995a), who documented that the results for both daily and monthly returns are inconsistent with the presence of herding behavior during periods of large price movements. By contrast, Chiang and Zheng (2010) find the existence of herd behavior in advanced countries (except US). Meanwhile, on the theoretical front, the approach of Christie and Huang has been improved upon by Chang et al. (2000). They modified the model in terms of the measurement of herding behavior and examine the up and down market for few different countries and found no evidence of herding behavior for US and Hong Kong. Thus, the evidence of herding phenomenon in the developed countries' markets is, at best, quite thin. Notable exceptions include the investigation on Japan, where partial herding has been detected. Also, South Korea and Taiwan appeared to display some symptoms of herding behavior. More recently, Galariotis et al. (2016) find no evidence of herding in G5 countries. However, the authors do note that herding for highly liquid stocks exists in most of these markets. The latter finding was corroborated for the Vietnamese market by Vo and Phan (2019) in addition to herding propensity in the general market.

The results of herding investigations in lesser developed markets, while still inconclusive, show greater variation. For instance, Purba and Faradynawati (2012) observed the existence of herd behavior in Indonesian market by using CCK model but found no existence of herd behavior using the CH model. Adopting a similar approach, Ahsan and Sarkar (2013) found no evidence of herding in Dhaka stock exchange. The contradictory conclusions derived from the CCK and CH model appear to be a recurring theme in emerging and frontier market literature when it comes to herding.

2.3. Types of herding

Two streams of theories are recognized in literature exploring the herding behavior; one is heading toward a particular stock, and the other is market-wide herding. Based on herding toward specific stock, individuals or a group of investors focus only on a subset of securities at the same time by abandoning other securities with identical characteristics. For the latter, research is focused on market-wide herding where investors follow market trends and tend to move with the actions of the market (Javaira and Hassan, 2016). The earliest methodological developments rely on Christie and Huang (1995b) who developed a model on herding for US stock market during the market stress by employing the cross-sectional standard deviation of return (CSSD) or depression to detect the herd behavior in the market. Following the finding of CH, Chang et al. (2000) investigate the herding behavior of the USA, Hong Kong, Japanese, South Korea and Taiwanese markets by modifying the study of Christie and Huang by employing Cross-sectional Absolute Deviation of returns (CSAD) instead of CSSD (Chang et al., 2000). In a related approach concentrating on the utility of advanced analytical tools vis-à-vis herding in markets, Chiang and Zheng (2010) found that sophisticated investors with access to high-quality microeconomic information were the least likely to engage in herding. Their finding relies on a study of 18 countries from 1988 to 2009.

2.4. Malaysia-specific evidence

Herding behavior of Malaysian investors has been examined by Lai and Lau (2004) by employing the cross-sectional standard deviation of returns, covering a period of ten years' monthly prices of all stocks from January 1992 to December 2000. They found the evidence of herding behavior in extreme lower market stress periods. Their result contradicts the findings of herd behavior as documented by Christie and Huang (1995b). On the other hand, the results also revealed that Malaysian investors acted according to their own opinions during periods of upper market stress as indicated by positive coefficient and they did not let their investment decisions be influenced much by the collective actions of the market (Lai and Lau, 2004). Herding behavior of foreign investors in Malaysia has been tested by Duasa and Kassim (2008). This estimation relied on a vector error correction model of foreign portfolio investment to capture the herding behavior. Their findings support the belief that there is a strong herd instinct prevailing among foreign investors in the Malaysian capital market. Thus far, previous studies on herd behavior are skewing toward developed countries and less attention has been paid to emerging markets such as Malaysia. Moreover, discoveries on herd behavior with respect to market uncertainty (crisis time) is extremely thin. Recent study of Omay and Iren (2019) investigates behavior of foreign investors in Malaysian stock market during the crisis. By employing a smooth-transition autoregressive and generalized impulse response function approach, they stated foreign investors exhibited herding behavior during Asian Crisis and responded more quickly than domestic investors toward the shock. But, the behavior of foreign investors was not different from Malaysian investors during the Global Financial Crisis. In a more recent study, Kumar et al. (2020) by using static and dynamic models, study the herding behavior in commodity markets of Asia–Pacific region (including Malaysia). The authors discriminate with respect to different market conditions. They noted the existence of herding in Chinese and Indonesian commodity markets. But, India, Malaysia and Taiwan expressed anti-herding behavior. Moreover, Japan does not convey the evidence of herding behavior, while Singapore and Thailand exhibit the herding during bearish markets only.

Linkage of herding behavior with social mood is a subject of study of Gavriilidis et al. (2016). Their study discussed the relationship of herding behavior during the holy month of Muslims (Ramadan) for seven countries (including Malaysia) and reported on the existence of stronger herding behavior within Ramadan month for the sample countries. Among studies that employ a regime dependent herding behavior approach for Malaysian market, a recent study of Kabir and Shakur (2018) investigated nonlinear herd behavior with regime switches for Asian and Latin American markets across market stress and volatility regimes. Their study report of not existing nonlinearity herding behavior, in contrast to previous findings, across market regimes for China, India, Malaysia, Singapore, Argentina and Brazil. Also, the same study finds that investors tend to herd during high volatile regimes for most of the investigated markets.

The existing stream of literature on Malaysian herding evidence leave several areas in need of attention. Firstly, lack of usage of long horizon data is noticeable. Secondly, the approaches are static in nature. We stress this point particularly because recent literature highlights the time-varying nature of herding. Thirdly, no sectoral decomposition has been observed in existing studies. As such, cross-sectional idiosyncrasies remain unexplored. Fourthly, Malaysia has emerged as a redoubtable hub for a niche financial asset class: Shariah-compliant assets. These stocks represent companies which operate in accordance with the Islamic principles. Many papers in the empirical finance domain have highlighted the diversification and hedging benefits offered by Islamic finance assets (Abu-Alkheil et al., 2017; Dewandaru et al., 2017). In the samples collected for the purpose of this paper, 171 stocks are identified which adhere to the Islamic principles and as such qualify as Shariah-compliant. There have been discussions in recent times in the resilience of this sector to global shocks and recessions (Hussain et al., 2015; Farooq and Zaheer, 2015; Baber, 2018). Therefore, we posit that investigation of herding phenomenon for this niche area is merited to enable better-informed decision about investing in Islamic stocks.

3. Methodology and data

3.1. Static approach

We describe our static modeling approach based on the methodology proposed by Christie and Huang (1995b) and by Chang et al. (2000); referred to hereafter as CH and CKK. CH proposed the use of cross-sectional standard deviation of returns (CSSD) to detect herd behavior, whereas CKK suggest the use of cross-sectional absolute deviation (CSAD) of returns. The authors of the latter approach remark that the two methods are analogous in spirit but do not always reach the similar conclusion.

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

Here $R_{i,t}$ is the observed stock return on firm i at time t and $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t. As a starting point in the analysis, this study illustrates the relation between CSAD and the market return. Let R_i denote the return on any asset i, R_m be the return on the market portfolio, and $E_{t(0)}$ denote the expectation in period t. A conditional version of the (Black, 1972) CAPM can be expressed as follows:

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0) \tag{2}$$

Where γ_0 is the return on the zero-beta portfolio, βi is the time-invariant systematic risk measure of the security, $I = 1; \ldots; N$ and $t = 1; \ldots; T$. Also, let β_m be the systematic risk of an equally-weighted market portfolio. Hence,

$$\beta_m = \frac{1}{n} \sum \beta_i \tag{3}$$

The absolute value of the deviation (AVD) of security i's expected return in period t from the tth period portfolio expected return can be expressed as:

$$\mathrm{AVD}_{i,t} = |\beta_i - \beta_m| E_t(R_m - \gamma_0) \tag{4}$$

Hence, the expected cross-sectional absolute deviation of stock returns (ECSAD) in period t can be defined as follows:

$$\mathrm{ECSAD}_t = \frac{1}{N} \sum \mathrm{AVD}_{i,t} = \frac{1}{N} \sum \beta_i - \beta_m \vee E_t\,(R_m - \gamma_0) \tag{5}$$

The increasing and linear relation between dispersion and the time-varying market expected returns can be easily shown as follows:

$$\frac{\partial \mathrm{ECSAD}}{\partial E_t\,(R_m)} = \frac{1}{N} \sum_{i=1}^{N} |\beta_i - \beta_m| > 0 \tag{6}$$

$$\frac{\partial^2 \mathrm{ECSAD}_t}{\partial E_t} \tag{7}$$

For the detection of herding as CH proposed, the following expression will be employed. Since, during periods of abnormally large average price movements or market stress, the differential predictions of rational asset pricing models and herd behavior are more pronounced, therefore, to detect the herding behavior the following equation is used:

$$S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon \tag{8}$$

Here,

${D_t}^L = 1$ if the market return on day t lies in the extreme lower tail of the return distribution;

${D_t}^L = 0$ otherwise;

${D_t}^U = 1$ if the market return on day t lies in the extreme upper tail of return distribution;

${D_t}^U = 0$ otherwise.

We divide the overall sample of 247 firms into several sub-samples: (i) first, according to Financial sectors, Manufacturing sectors, Shariah-compliant, and Shariah-non-compliant sectors; and thereafter (ii) we compile tercile portfolios as per market capitalization into large-cap, mid-cap, and small-cap portfolios. It is worth pointing out that when the sampling window began (1995), Bursa Malaysia used to be called Kuala Lumpur Stock Exchange. Although Bursa Malaysia has close to a thousand listed companies as of 2019, the choice to include the 247 sample firms is based on the dual justification of avoiding survivorship bias and data availability which enables us to cover until end of 2016. The data has been sourced from Thomson Reuters DataStream.

3.2. Dynamic approach

Having outlined the static (classical) approaches of CSAD and CSSD, we now outline the dynamic capture of herding via a regime-switching model. Using a regime-dependent approach to model herding behavior is gaining attention in recent times due to its flexibility and power in explaining herding under different states. For instance, for emerging markets, the CSAD approach was extended by Youssef and Mokni (2018) under a regime-switching framework to investigate herding in the Gulf Cooperation Council (GCC) stock markets. While our erstwhile approach relies on constant parameters for our sampling window, now we discriminate between bullish and bearish market regimes whereby herding may or may not take place in either/both regimes. Accordingly, how two-state Markov-Switching model for CSAD dispersions is as follows:

$$Dispersion_t = \alpha_{0,r} + \beta_{1,r,t} \vee R_{market} \vee + \beta_{2,r,t} R^2_{market} + \varepsilon_t \tag{9}$$

The final term in the equation above is an error term with a zero mean and fixed standard deviation that is independent and identically distributed, while r is a regime indicator with discrete value of 0 of 1 indicating a two-state first order Markov chain. Since we intend to subject both CH and CCK models to the regime-dependent framework, we use the notation $Dispersion_t$ in Eq. (9) to denote operationalization of CSAD and CSSD respectively. This leads us to Markov chain transition probabilities as:

$$p_{xy} = P\left(Stock_t = y\right) \tag{10}$$

Here, x and y take on the regime-specific discrete values of 0 or 1, while p_{xy} expresses the transition probability of the chain. In other words, it expresses the probability of regime x occurring at $t + 1$ provided that the market was in regime y at time t. The transition probability matrix above satisfies the total probability requirement of 1. It is worthy to mention there are three reasons for why the new model of herding behavior is better than the existing model. Firstly, as stated by CCK (2000) herding approach of CH is proven to be a less stringent approach to detect herding behavior. Therefore, we incorporate it in our analysis to examine and compare with our approach with respect to emerging markets. Secondly, many studies argue that herding behavior has various drivers other than return (see Youssef and Mokni, 2018, for more details) which are related to market conditions. In fact, during periods of market stress the speculation activities contribute more forcefully to market uncertainty and can precipitate a feedback loop. Hence, herding behavior would be more common during the down market. Therefore, the research at hand takes into consideration of this argument and employs a regime-switching approach to detect herding behavior. Finally, nonlinearity of herding behavior is captured via CSAD but tendency of herding behavior under different market regimes is only capturable through a model that allows parameters to vary according to a regime-switch.

4. Results and analyses

Table 1 presents the descriptive statistics of the study. Based on the daily nature and period of study, from the standard deviation for different samples it could be said, the Shariah compliant stock has the nearest amount of return to the average of return distribution during the period of study as compared to the conventional stocks.

Figs. 1 and 2 below show the hexagonal binning plot of the cross-sectional standard deviation of return and cross-sectional absolute deviation of return for the study for the whole market and relevant sectors. Next, we present the results for the static modeling based on classical approaches of CCK and CH. To make the results more practice-relevant, we present the results accompanied by dummy variables capturing extreme upward or downward movements. We achieve this by analyzing the dispersion of returns and see whether it increases or decreases. Our daily data regressions in Table 2 show positive and statistically significant coefficients for UP and DOWN markets, which means that stock returns dispersions empirically increase rather than decrease in both directions of extreme market movement. This implies evidence against the existence of herding. Similar results are observed when we disaggregate the samples according to Shariah compliant and non-compliant stocks. Interestingly, however, the financial and manufacturing sector stocks exhibit mild herding tendencies in upward market in the CH approach. By contrast, most of the results in the CCK models exhibit mild to strong evidence of herding as expressed by the negative coefficients. Moreover, these occur largely in the up-market scenarios.

Findings of our tests are consistent with the finding of Purba and Faradynawati (2012), who too found inconsistencies in the results of the aforesaid competing models for the Indonesian stock market. These results are somewhat puzzling because an impressive body of finance literature documents rising correlation and contagion on a broad market basis (and also in the financial sectors) during crisis periods (Hwang and Salmon, 2004; Zhou and Lai, 2009). Our anomalous result could be an idiosyncrasy of the Malaysian market or could be a short-coming of the static modeling approach. Moreover, with a few minor exceptions, nearly all static models suffer from poor explanatory power as manifested by R2 values. These issues become even more glaring as we compare the static results with those from Markov-Switching approach presented below in Tables 3 and 4. Overall, the static modeling results based on both classical approaches concur that the financial and manufacturing sector exhibit herding tendencies during bullish market periods.

In accordance with the a priori stipulation of two regimes in our regime-switching herding model, we estimate the likelihood of each model through non-linear optimization as per Newton–Raphson technique. Next, we carry out the calculation of expectation under a particular regime based on the current estimates of the corresponding parameters. We do this by assigning each joint incidence of CSAD/CSAD versus market returns to one of the bullish or bearish regimes. Afterwards we maximize the parameters conditioned on the values from each state by obtaining new estimates from OLS regressions and proceed to Markov-Switching results for each regime until convergence is achieved. It is worth noting that, as shown in Eq. (9) above, we

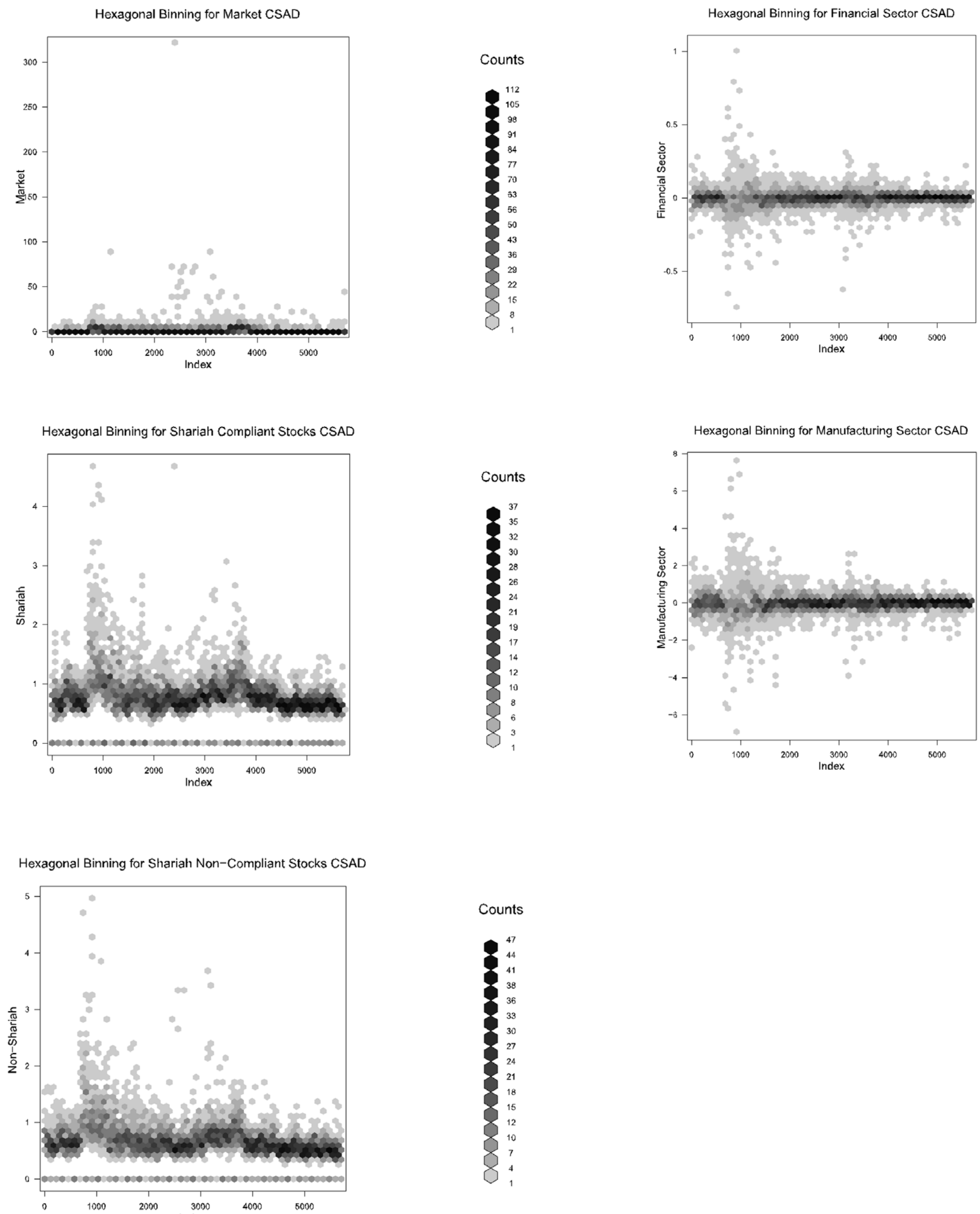

Fig. 1. Distributive properties of CSAD values via hexagonal binning.

Table 1
Descriptive statistics.

	n	Mean	SD	Median	Trimmed	MAD	Max.	Range	Skew	Kurtosis	S.E.
Panel A: CSAD											
Market	5703	2.411	5.836	1.507	1.738	0.865	320.287	320.287	31.984	1580.603	0.077
Financial sector	5703	−0.001	0.066	0.000	−0.001	0.033	0.994	1.738	0.723	29.804	0.001
Manufacturing sector	5703	−0.011	0.600	0.000	−0.013	0.291	7.573	14.492	0.538	25.833	0.008
Shariah	5703	0.810	0.386	0.758	0.785	0.221	4.657	4.657	1.804	11.549	0.005
Non-Shariah	5703	0.697	0.365	0.646	0.669	0.216	4.941	4.941	2.337	15.790	0.005
Panel B: CSSD											
Market	5703	1.129	0.796	1.008	1.051	0.348	16.545	16.545	7.159	101.000	0.011
Financial sector	5703	0.001	0.066	0.002	0.001	0.034	0.986	1.728	0.704	28.957	0.001
Manufacturing sector	5703	−0.015	0.666	0.000	−0.015	0.312	8.429	17.305	0.117	28.311	0.009
Shariah	5703	−0.012	0.672	0.000	−0.016	0.330	8.503	16.087	0.531	25.378	0.009
Non-Shariah	5703	−0.011	0.647	0.000	−0.012	0.320	8.757	16.575	0.696	27.349	0.009

Figs. 1 and 2 below show the hexagonal binning plot of the cross-sectional standard deviation of return and cross-sectional absolute deviation of return for the study for the whole market and relevant sectors.

include a polynomial term to test for non-linearity. This decision is undertaken after establishing that including a non-linear term

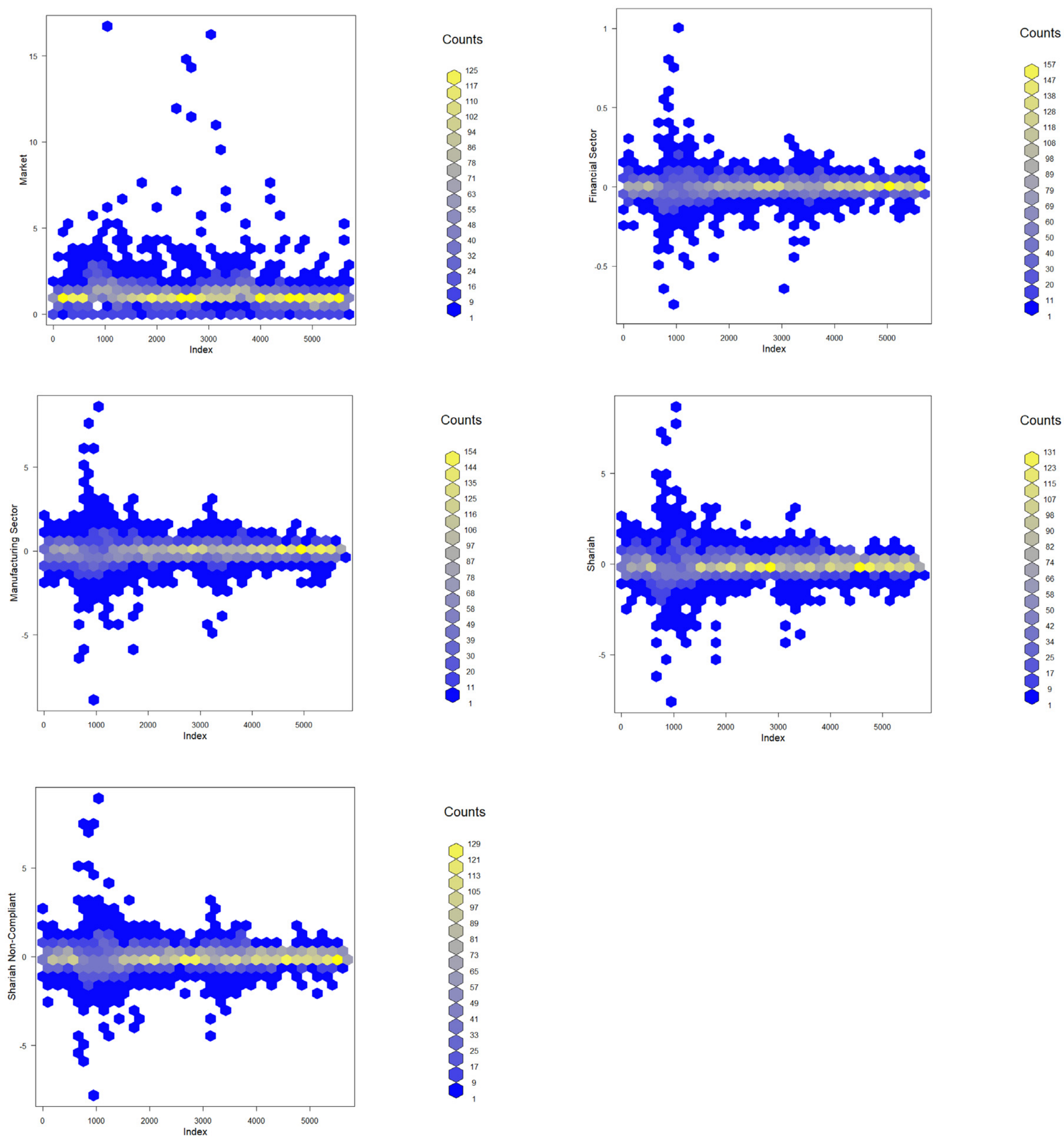

Fig. 2. Distributive properties of CSSD values via hexagonal binning.

would indeed result in a better model compared to the static linear coefficient model in classical CH or CCK approaches. We present our results based on p-values relying on Chi-squared distribution and approximate upper bound for the significance level of the Log-Likelihood ratio. Additionally, we use Akaike Information Criterion to substantiate the choice of two states after accounting for non-linearity. In this regard, we heed the advice of previous statistical researchers who present Monte Carlo evidence of the superiority of AIC results in choosing the appropriate model.

The results in Table 3 for CSAD-based model confirms the static model's report on presence of herding in financial and manufacturing sector in bullish market regimes. Similar coefficients are observed for the large and mid-cap portfolios. Surprisingly, no herding evidence is documented in bear market scenarios. Interestingly, however, in bullish regimes, volatility in the broad market, shariah, and non-shariah stocks exhibit herding tendencies. Much stronger evidence of volatility herding is recorded in bearish regimes as per coefficients of manufacturing sector, large-cap, and mid-cap portfolios.

Meanwhile, Table 4 results for CSSD-based dynamic modeling suggests somewhat subdued evidence of non-linearity but captured much stronger propensity for herding in bearish regimes. In fact, in down-market scenario, vast majority of market segments and portfolios suggest herding tendencies, while volatility herding is marginally more prominent in up-market scenarios. Transition probability matrices (shown in Table 5 below) suggest a strong propensity of most sectoral decompositions coefficients to persist with the existing regimes.

There is also a theoretical/methodological implication of our results. As an anonymous referee points out, the Markov-Switching results resemble closer the CSAD results rather than CSSD. There are two main reasons for this. First is the incorporation of non-linear (squared market returns) term in the CSAD model, which accords with our regime-switching approach's incorporation of non-linearity. Second, earlier empirical works, in addition to Christie and Huang's seminal work, show that the

Table 2
Static modeling results.

Panel A: Christie and Huang approach

	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	1.2663*** (0.0102)	1.3228*** (0.0107)	1.0673*** (0.0101)	0.0037** (0.0012)	0.02708 (0.01851)	0.0058*** (0.0009)	0.0188*** (0.0051)	0.8132*** (0.0912)
UP	0.5908*** (0.0381)	0.6989*** (0.0466)	1.2939*** (0.0660)	−0.0200*** (0.0027)	−0.1461*** (0.02524)	−0.0895*** (0.0000)	−0.1237** (0.09125)	0.7123*** (0.09942)
DOWN	0.9264*** (0.0441)	0.9259*** (0.0466)	1.2907*** (0.0637)	0.0072*** (0.0006)	0.05373*** (0.00592)	0.0039** (0.0019)	0.08457*** (0.02157)	0.31218* (0.14541)
R^2	10.12%	9.34%	11.95%	2.44%	15.22%	11.84%	10.69%	8.94%

Panel B: CCK approach

	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	2.0143*** (0.0795)	0.7273*** (0.0052)	0.6525*** (0.0038)	0.0060*** (0.0012)	0.01955 (0.01208)	0.12184 (0.0932)	0.2337** (0.1048)	0.3215** (0.1804)
UP	−1.2940*** (0.15724)	−0.3659*** (0.0117)	0.4619*** (0.0100)	−0.02017*** (0.0028)	−0.14923*** (0.02815)	−0.1183*** (0.0048)	−0.2191*** (0.0845)	−0.3614** (0.1751)
DOWN	2.6419*** (0.1773)	0.2828*** (0.0089)	−0.4377*** (0.0107)	0.0071*** (0.0006)	0.04881*** (0.0659)	0.14982 (0.11285)	0.08423** (0.04517)	0.09845 (0.07413)
R^2	4.54%	19.09%	39.37%	2.97%	19.46%	11.25%	18.34%	21.06%

Table 3
Dynamic herding model results for CSAD.

Panel A: Regime 1

	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	1.1217*** (0.0140)	0.5337*** (0.0112)	0.5105*** (0.0035)	0.0058*** (0.0001)	0.0000 (0.0002)	0.0939** (0.0598)	0.0000 (0.0031)	0.1139*** (0.0008)
β_1	0.6384*** (0.0317)	1.0142*** (0.0276)	0.3864*** (0.0100)	−0.0956*** (0.0018)	−0.9149*** (0.0013)	−0.1458*** (0.0032)	−0.2138** (0.1451)	0.8015*** (0.1012)
β_2	−0.0230*** (0.0069)	−0.1263*** (0.0074)	−0.0049 (0.0036)	0.0007 (0.0005)	0.0003 (0.0004)	0.0843** (0.0322)	0.1215*** (0.0080)	−0.2021*** (0.0089)
R^2	47.18%	61.16%	67.69%	74.62%	91.68%	29.90%	48.51%	60.54%

Panel B: Regime 2

	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	1.6040*** (0.1679)	0.6201*** (0.0033)	0.4983*** (0.0110)	−0.0026** (0.0009)	−0.0024** (0.0008)	−0.3687*** (0.0547)	−0.4213*** (0.0089)	0.5123*** (0.0083)
β_1	3.0301*** (0.6460)	0.3751*** (0.0081)	0.7477*** (0.0236)	0.0867*** (0.0018)	0.9228*** (0.0017)	0.1219** (0.0641)	0.2169** (0.1032)	0.0812*** (0.0031)
β_2	−0.6359* (0.2620)	0.0097*** (0.0014)	−0.0432*** (0.0044)	0.0020*** (0.0004)	−0.0027*** (0.0004)	−0.1882*** (0.0054)	−0.0984** (0.0350)	0.1192** (0.0547)
R^2	66.19%	77.25%	58.20%	76.46%	99.69%	58.13%	61.86%	71.83%
AIC	−2868.33	−2340.586	−2350.069	−21687.27	−17950.33	−2125.842	−2258.315	−2408.108
LL	6428.164	1176.293	1181.034	10849.64	8981.163	9284.126	7165.622	9984.087

classic (CSSD) approach can suffer from a low power due to its reliance on dummy variable. As a matter of fact, modern empirical works appear to be favoring a quantile-specific approach in overcoming this issue while maintaining CSSD's dummy flavor. Though not the subject of present investigation, it is also possible to work around this low power by incorporating a Bayesian approach or employing skewed-t innovations. Additionally, CSAD approach also exhibits higher statistical power since it is better equipped to detect sentiment synchronization in normal markets instead of CSSD's binary distinction of extremes of 1% upper and 1% lower returns. Overall, results from Markov-Switching models indicate substantial evidence of non-linearity and regime-dependent existence of herding in both market-wide returns and volatility. Moreover, the explanatory power of the results is heavily acceptable compared to static modeling. These results underscore both the methodological constraints of the classical approach and the cost of ignoring the regime-dependent nature of herding as a market phenomenon.

5. Conclusion

Motivated by the surge of capital flow to emerging capital markets among plummeting yields in the developed economies in recent years, we study the herding phenomenon in an important emerging stock exchange: Bursa Malaysia. Based on a daily dataset from 1995 to 2016, we employ initially two seminal and competing models of measuring herding behavior in the stock market. We find that the models reveal inconsistent and conflicting results. We highlight the paucity of explanatory power of these two popular testing approaches by adopting an alternative Markov-Switching specification of the static herding models which enable us to derive inferences about herding propensity under multiple market regimes. Our regime-specific approach is tethered to the premise of time-varying nature of herding and the fact that extreme episodes such as bubbles and crashes invite varied herding tendencies. Though overall results indicate lack of support for broad-market herding in Malaysia, our results from the dynamic modeling approach reveals substantial non-linearities and evidence of greater herding during high volatility

Table 4
Dynamic herding model results for CSSD.

Panel A: Regime 1								
	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	1.0785*** (0.0061)	−0.0045* (0.0020)	−0.0079 (0.0050)	−0.0005 (0.0009)	0.0081*** (0.0024)	−0.0587 (0.0648)	0.0519*** (0.0004)	−0.2153*** (0.0912)
β_1	0.3456*** (0.0138)	1.0338*** (0.0044)	0.9459*** (0.0100)	0.0867*** (0.0019)	−0.9958*** (0.0056)	0.1285** (0.0531)	−0.6258*** (0.0325)	0.8123*** (0.0211)
β_2	0.0244*** (0.0028)	−0.0040*** (0.0009)	0.0069** (0.0021)	0.0020*** (0.0004)	−0.0150*** (0.0015)	0.0841*** (0.0000)	−0.1139*** (0.0215)	−0.1282*** (0.0908)
R^2	51.19%	93.84%	91.99%	75.51%	97.48%	88.41%	70.59%	90.27%
Panel B: Regime 2								
	Market	Shariah	Non-Shariah	Finance	Manufacturing	Large Cap	Mid Cap	Small Cap
Intercept	1.1447*** (0.0356)	0.0013 (0.0018)	0.0227*** (0.0045)	0.0079*** (0.0009)	−0.0158*** (0.0003)	0.8421*** (0.1125)	−0.2871*** (0.0989)	0.0912** (0.0421)
β_1	1.6717*** (0.0945)	−1.0218*** (0.0041)	−0.9876*** (0.0097)	−0.0959*** (0.0019)	0.0059*** (−0.011)	−0.2247*** (0.0984)	0.1648*** (0.0419)	−1.1287*** (0.0088)
β_2	−0.2606*** (0.0257)	0.0004 (0.0011)	0.0047 (0.0025)	0.0008 (0.0005)	−0.0111*** (0.0012)	0.2369** (0.1305)	−0.3135*** (0.0878)	0.0217*** (0.0032)
R^2	23.09%	98.63%	92.01%	73.73%	97.03%	81.62%	90.12%	91.27%
AIC	−7576.469	−8643.32	−885.3915	−21452.4	−5577.845	−2891.369	−2764.215	−2661.692
LL	3782.234	4327.66	448.695	10732.202	2794.923	2871.323	2551.089	3308.213

Table 5
Inter-regime transition probabilities.

		Market		Shariah		Non-Shariah		Finance		Manufacturing		Large-Cap		Mid-Cap		Small-Cap	
CSAD		1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
	1	0.96	0.34	0.84	0.10	0.89	0.19	0.70	0.36	0.58	0.43	0.81	0.35	0.68	0.24	0.71	0.33
	2	0.04	0.66	0.16	0.90	0.11	0.81	0.30	0.64	0.42	0.57	0.19	0.65	0.32	0.76	0.29	0.67
CSSD		1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
	1	0.86	0.31	0.57	0.40	0.61	0.35	0.66	0.30	0.62	0.41	0.68	0.39	0.81	0.28	0.77	0.36
	2	0.14	0.69	0.43	0.60	0.39	0.65	0.34	0.70	0.38	0.59	0.32	0.61	0.19	0.72	0.23	0.64

Note: This table presents the Markov-chain based transition probability matrices from regime 1 to regime 2 based on the alternative specifications of CSAD and CSSD herding models.

regimes. Sector-wise, the financial and manufacturing segments of the market are most prone to herding, while capitalization-wise, large and mid-cap portfolios herd more in bullish markets. Findings of our tests are consistent with the finding of Purba and Faradynawati (2012), who too found inconsistencies in the results of the aforesaid competing models for the Indonesian stock market. To advance the literature on herding in emerging or frontier markets further, we invite future researchers to investigate herding phenomenon at intraday level using high-frequency data (Hsieh, 2013). We intend to do the same for the Malaysian market in an upcoming paper. Another interesting angle to extend the scope of herding in equity markets can be via the approach taken by Voukelatos and Verousis (2019), who show that information contained in options can significantly coincide with herding behavior in the advanced markets. Though highly promising, this track can suffer from thin data obstacles in emerging markets which have mostly an undeveloped derivative market environment.

CRediT authorship contribution statement

Abdollah Ah Mand: Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Imtiaz Sifat:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing.

References

Abu-Alkheil, A., Khan, W.A., Parikh, B., Mohanty, S.K., 2017. Dynamic co-integration and portfolio diversification of Islamic and conventional indices: Global evidence. Q. Rev. Econ. Finance 66, 212–224.

Ahsan, A.F.M.M., Sarkar, A.H., 2013. Herding in Dhaka stock exchange. J. Appl. Bus. Econ. 14 (2), 11–19.

Baber, H., 2018. How crisis-proof is Islamic finance? A comparative study of Islamic finance and conventional finance during and post financial crisis. Qual. Res. Financial Mark. 10 (4), 415–426.

Balcilar, M., Demirer, R., Hammoudehc, S., 2013. Investor herds and Regime-switching: Evidence from Gulf arab stock markets. J. Int. Financial Mark. Inst. Money 23 (1), 295–321.

Black, F., 1972. Capital market equilibrium with restricted borrowing. J. Bus. 45 (3), 444–455.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Financ. 24 (1), 1651–1679.

Chen, G., Rui, O.M., Xu, Y., 2003. When will investors herd? Evidence from the Chinese stock markets. J. Financial Res. 37 (1), 2–40.

Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. J. Bank. Financ. 34 (1), 1911–1921.

Christie, W.G., Huang, R.D., 1995a. Do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37.

Christie, W.G., Huang, R.D., 1995b. Following the pied piper: Do individual returns herd around the market? Financ. Anal. J. 51 (4), 31–37.

Dang, H.V., Lin, M., 2016. Herd mentality in the stock market: On the role of idiosyncratic participants with heterogeneous information. Int. Rev. Financ. Anal. 48, 247–260.

Demirer, R., Kutan, A.M., 2006. Does herding behavior exist in Chinese stock markets? Int. Financial Mark. Inst. Money 16 (1), 123–142.

Devenow, A., Welch, I., 1996. Rational herding in financial economics. Eur. Econ. Rev. 40 (3–5), 603–615.

Dewandaru, G., Masih, R., Bacha, O.I., Masih, A.M.M., 2017. The role of Islamic asset classes in the diversified portfolios: Mean variance spanning test. Emerg. Mark. Rev 30, 66–95.
Duasa, J., Kassim, S., 2008. Herd Behaviour in Malaysian Capital Market: An Empirical Analysis. Munich Personal RePEc Archive 13303, pp. 1–18.
Economou, F., Gavriilidis, K., Kallinterakis, V., Yordanov, N., 2015. Do fund managers herd in frontier markets—and why? Int. Rev. Financ. Anal. 40, 76–87.
Fama, E.F., Fisher, L., Jensen, M.C., Roll, R., 1969. The adjustment of stock prices to new information. Internat. Econom. Rev. 10 (1), 1–21.
Farooq, M., Zaheer, S., 2015. Are Islamic banks more resilient during financial panics? Pac. Econ Rev. 20 (1), 101–124.
Galariotis, E.C., Krokida, S.I., Spyrou, S.I., 2016. Herd behavior and equity market liquidity: Evidence from major markets. Int. Rev. Financ. Anal. 48, 140–149.
Gavriilidis, K., Kallinterakis, V., Tsalavoutas, I., 2016. Investor mood, herding and the Ramadan effect. J. Econ. Behav. Organ. 132, 23–38.
Hsieh, S.F., 2013. Individual and institutional herding and the impact on stock returns: Evidence from Taiwan stock market. Int. Rev. Financ. Anal. 29, 175–188.
Hussain, M.M., Shahmoradi, A., Turk, R., 2015. An Overview of Islamic Finance (No. 15–120). International Monetary Fund.
Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Financ. 11 (4), 585–616.
Javaira, Z., Hassan, A., 2016. An examination of herding behavior in Pakistani stock market. Int. J. Emerg. Mark. 10 (3), 474–490.
Kabir, M.H., Shakur, S., 2018. Regime-dependent herding behavior in Asian and Latin American stock markets. Pac.-Basin Finance J. 47, 60–78.
Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47 (2), 263–292.
Kaminsky, G., Schmukler, S., 1999. On Financial Booms and Crashes: Regional Patterns, Time Patterns, and Financial Liberalization. Manuscript. The World Bank.
Keynes, J.M., 1930. The Great Slump of 1930.
Kumar, A., Badhani, K.N., Bouri, E., Saeed, T., 2020. Herding behavior in the commodity markets of the Asia-Pacific region. Finance Res. Lett. 101813.
Lai, M.-M., Lau, S.-H., 2004. Herd behavior and market stress, the case of Malaysia. Acad. Account. Financial Stud. J. 8 (3), 85–102.
Nasarudin, A.F., Noordin, B.A.A., Law, S.H., Yahya, M.H., 2017. Investigation of herding behaviour in developed and developing countries: Does country governance factor matters?. Cap. Mark. Rev. 25 (2), 1–14.
Nassir, A.M., 2002. Is the Klse Efficient? Efficient Market Hypothesis Vs Behavioural Finance.
Ngoc, L.T.B., 2014. Behavior pattern of individual investors in stock market. Int. J. Bus. Manag. 9 (1), 1–16.
Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. J. Finance 53 (6), 1887–1934.
Omay, T., Iren, 2019. Behavior of foreign investors in the Malaysian stock market in times of crisis: A nonlinear approach. J. Asian Econ. 60, 85–100.
Purba, A.V., Faradynawati, I.A.A., 2012. An examination of herd behavior in the Indonesian stock market. Indones. Cap. Mark. Rev..
Rülke, J.C., 2013. Do corporate profit forecaster herd?—Evidence from Canada, UK and the United States. Int. J. Finance Econ. 18 (1), 93–102.
Stankov, L., Lee, J., 2014. Overconfidence across world regions. J. Cross-Cultural Psychol. 45 (5), 821–837.
Vo, X.V., Phan, D.B.A., 2019. Herding and equity market liquidity in emerging market. Evidence from Vietnam. J. Behav. Exp. Finance.
Voukelatos, N., Verousis, T., 2019. Option-implied information and stock herding. Int. J. Finance Econ..
Wong, Y.-C., Kok, K.-L., 2009. Herding measures in equity markets: A case study of Bursa Malaysia. Labu. Bull. Int. Bus. Finance 7, 13–32.
Youssef, M., Mokni, K., 2018. On the effect of herding behavior on dependence structure between stock markets: Evidence from GCC countries. J. Behav. Exp. Finance 20, 52–63.
Zhou, R.T., Lai, R.N., 2009. Herding and information based trading. J. Empir. Financ. 16 (3), 388–393.