The evolution of herd behavior: will herding disappear over time?

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Abstract

Purpose – The purpose of this paper is to examine the evolutionary nature of herding phenomenon in the context of a frontier stock market, the Colombo Stock Exchange of Sri Lanka.

Design/methodology/approach – This study applies the cross-sectional absolute deviation methodology for daily frequencies of data of all the common stocks listed during the period from April 2000 to March 2018. The regression coefficients are estimated by using both the ordinary least square and the quantile regression procedures.

Findings – The findings reveal significant changes to the pattern of herding over different market periods, each with specific characteristics. Herding is strongly evident in up and down market days in the 2000-2009 period, during which the market was highly uncertain with the impact of the political instability of the country due to the Civil War on the stock trading. Even after this Civil War period, herd tendency is strongly manifested toward the up market direction as a result of the investors' optimism about the country's economy and political stability, which caused to a speculative bubble in the market. After that, it is turned into negative herding due to the panic selling occurred in view of the uncertainty of the inflated prices, which led to a market crash. Notably, herding appears to be consistently absent over the period after the crash, despite the presence of herd motives such as high market uncertainties triggered by political instability and economic crisis during that period.

Research limitations/implications – The findings suggest that herd behavior is an evolving phenomenon in financial markets. Consistent with the adaptive market hypothesis, the absence of herding evident after the market crash could be attributed to the investors' learning of the irrationality of herding/negative herding for adapting to market conditions. As a result, herding and negative herding tendencies declined and disappeared at the aggregate market level.

Originality/value – This study contributes to the literature by providing novel evidence on the evolutionary nature of behavioral biases, particularly herding, as predicted by the adaptive market hypothesis. With the application of the quantile regression procedure, in addition to customary used ordinary least squares approach, it also provides robust evidence on this phenomenon.

Keywords Quantile regression, Adaptive market hypothesis, Colombo stock exchange, Frontier market, Herd evolution, Market bubble and crash, Investor learning, Negative herding

Paper type Research paper

1. Introduction

Behavioral economics, a branch of economics that blends insights of psychology and economics, attempts to explore how, when and why individuals behave irrationally when making decisions. The theories and concepts of behavioral economics have greatly contributed to the development of behavioral finance which strives to find answers for

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the irrationality of the participants in financial markets. Over the past few decades, the behavioral finance researchers have dedicated appreciable attention for understanding the behavior of market participants and biases associated with their actions when dealing with financial assets. Their findings reveal that such biases occur due to limitations of the inner cognitive abilities and psychological states as well as effects of external stimuli, for example, market conditions, social structures and information asymmetry. These findings, while challenging the "rational expectation" notion of the efficient market hypothesis, support the prediction of behavioral finance that the market participants' behavior is bounded rational, which results to maladaptive decisions and eventually leads to poor performance. Based on the concept of bounded rationality and some principles of evolutionary biology and evolutionary psychology, Lo (2004, 2005, 2012) introduced a new paradigm called "adaptive market hypothesis" (AMH) to reconcile this debate between the efficient market hypothesis and the behavioral finance.

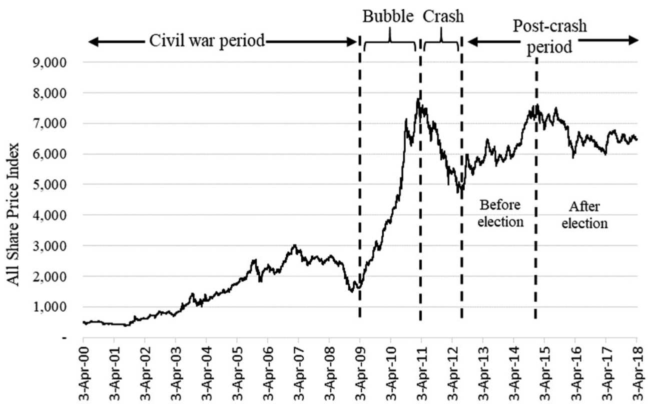
The AMH assumes that the rationality of market participants' behaviors, thereby, efficient functioning of a financial market is an evolving phenomenon, driven by market forces and the market participants' adaptability to the environment in which they behave. According to this theory, investment strategies (heuristics) become biased or irrational when they do not fit with the context to which they apply. Their impacts to market prices depend on the proportion of the population with biased heuristics verses the proportion of the competing population with more effective heuristics that are adaptive to market conditions. The evolutionary perspective of this theory implies that competition drives the market participants who are susceptible to biases, to learn from their biases for adapting to the market conditions. Accordingly, given enough time and competitive market forces, the market participants who cannot adapt will exit from the market due to losses. Thus, the market will eventually consist of those who adapt to its conditions with appropriate heuristics. Consequently, behavioral biases would decline in the market and, thereby, prices would approach to their rational level.

One of the behavioral biases extensively discussed in the behavioral finance literature is herding. It is one's propensity to abandon own information and belief and imitate the actions of others in making choices. This behavioral tendency has been vastly studied in both developed and emerging financial markets. However, it has limitedly been explored in respect of frontier stock markets, a category of markets which is predicted to be more vulnerable for that when compared to developed and emerging markets (Economou, 2016; Guney *et al.*, 2017). Further, based on the evolutionary perspective of the AMH, herding would follow an evolving path, in the sense that it would tend to decline and disappear through the competition and the adaptation of market participants' behaviors. However, this evolution phenomenon, to the best of my knowledge, has not been much supported with empirical evidence at the aggregate market level. Therefore, this study aims to explore the evolution of herding in the stock market of Sri Lanka, a frontier market[1], formally known as the Colombo Stock Exchange (CSE).

The CSE is an ideal ground for the examination of the evolution of herding due to the following reasons. First, as discussed in Section 3, it, as a pre-emerging market, is small and illiquid, as characterized by low capitalization, low trading volume and relatively few number of stocks actively traded, which could discourage investor participation for investing and trading activities. In addition, the market is regularly exposed to certain risks that may cause incidents such as information asymmetry, insider trading, low transparency, price manipulations and significant mispricing. These conditions would impair both the amount and the trustworthiness of the information generated, eventually rendering to a more ambiguous informational environment in the market. As a result, the investors would tend to herd for resolving this information uncertainty (Guney *et al.*, 2017). Second, over the last two decades, the trading environment of the CSE has been highly uncertain owing to incidents of political instability and economic crises of the country. Given such stressful environment, it is also more probable that the investors disregard their own beliefs and are prone to imitate others' behaviors when making their trading decisions (Arjoon and Bhatnagar, 2017; Hwang and Salmon, 2004; Olsen, 2011). Third, the previous studies on the CSE find both the evidence of herding and the absence of it over different market periods (Sewwandi, 2016; Xiaofang and Shantha, 2017, 2018) and the investors' tendency to learn the irrationality of such behavior (Shantha, 2019), which can be considered as some clues of the evolution of herd behavior in the market.

Accordingly, a longer sample period, from April 2000 to March 2018 which cover different uncertain episodes of the CSE (Figure 1), was chosen in this study in an attempt to detect herd evolution in the market. The findings reveal that herding, which triggered during the period of political instability due to Civil War and the market bubble period, turns into negative herding during the subsequent market crash period. It, however, appears to be consistently absent during the period after the crash despite the presence of herd motives such as market uncertainties due to the political instability and economic crisis of the country during this period. Hence, these results validate the prior evidence obtained at the individual investor level that indicates the investors' tendency to get away from herding by learning its irrationality from the experiences of losses and associated psychological shocks (Shantha, 2019). Accordingly, the findings provide a strong support for the evolutionary nature of behavioral biases, as implied by the AMH.

The findings of this work contribute the literature in the following ways. First, this study addresses a relatively underexplored behavioral finance concern on the evolutionary nature of behavioral biases, as predicted by the AMH. Hence, while supporting this evolutionary perspective, the findings will enhance the understanding of the nature of behavioral biases, particularly herding phenomenon in financial markets. Second, the previous studies conducted at the aggregate market level suggest the regulatory reforms subsequent to a market crisis period as a turning point for herd evolution[2]. On the contrary, the findings of this study reveal the absence of herding during the period after the market crash even though the market was not undergone



Note: This figure plots the movements of the All share price index, a value-weighted index representing all the stocks listed on the CSE, over the period from April 2000 to March 2018t

Figure 1. Movement of market index of the CSE

significant regulatory reforms over that period. Thus, with the support of prior evidence reported at the individual investor level (Shantha, 2019), the results imply the investors' mistake-learning behavior as another possible way of herd evolution in financial markets. Third, unlike previous studies conducted on the CSE (Sewwandi, 2016; Xiaofang and Shantha, 2017), the present study examines herd behavior during different market episodes of the CSE over a long period. Thus, with the evidence on herd evolution across different market episodes, it provides an explanation for the mix empirical findings on herding, as reported by those previous studies. Fourth, the quantile regression (QR) procedure is employed in this study, in addition to customary used the ordinary least squares (OLS) approach. Hence, the findings contribute the literature in terms of not only robust evidence but also a deeper knowledge of herd behavior in the frontier market setting. Accordingly, the findings will enlarge and enrich the behavioral finance literature, facilitating further understanding of herding phenomenon in financial markets.

The remainder of the paper is organized as follow. Section 2 reviews the literature about causes of herding and how it would evolve in a financial market. Section 3 explains the nature of the investment environment of the CSE and how it is likely to stimulate herd behavior during the sample period. While discussing about the data in Section 4, Section 5 presents the methodology employed in this study. The empirical results are reported in Section 6. Section 7 concludes the paper with the empirical implications. The limitations of the current study and the direction for future research are given in Section 8.

2. Literature review

Herding is observable as correlated behaviors of a group of investors, occurred consciously or unconsciously, as they trade in the same direction at the same time. (Hwang and Salmon, 2004; Nofsinger and Sias, 1999). It, by becoming a market-wide trend, appears as convergence of investors' behaviors towards consensus at the aggregate market level (Chang *et al.*, 2000). The literature reveals that investors' cognitive limitations, psychological state and external factors such as market conditions, social interactions and information asymmetry are driving forces of herd behavior in financial markets. Some of these causes can be comprehended through the behavioral models of Barberis *et al.* (1998), Daniel *et al.* (1998), Hong and Stein (1999) and Lam *et al.* (2010, 2012). These models demonstrate how investor sentiment leads to conservatism and representativeness biases when updating their beliefs. The conservatism bias causes too slow in updating beliefs with new information, thus, overweighs past information while underweighting new information. In case of representativeness bias, investors tend to overweigh the recent information and underweight their past beliefs, thus, update their beliefs too quickly with a small sample of recent observations. Accordingly, the investors who behave too conservatively tend to follow the information implicit in past stock prices, and those who are subject to representativeness bias tend to react based on new information. Hence, their actions can correlate unconsciously due to the similarity of information employed in their decision-making. These models also predict that the conservatism and representativeness biases lead to short-term momentum and long-term overreaction and reversal of prices. Then, the momentum traders would enter into market with trend chasing strategies to reap profit opportunities resulting from the short-term price momentum, which can also appear as correlated trading patterns in the market. The resulting excessive momentum in prices and representativeness bias eventually lead to long-term overreactions and subsequent reversal of prices, thereby, increasing market volatility. Consequently, the investors may become unsure of how to react to this increased uncertainty. Thus, they may tend to suppress their own belief and imitate the behaviors of others in the market.

The following sections review the literature relating to causes of herding and how the evolutionary nature of this phenomenon can be expected in financial markets.

2.1 Herding as rational heuristic versus irrational emotional response

Herd behavior occurs as a rational heuristic or an irrational emotional response of market participants. Concerning on the rational side of herding, investment professionals tend to herd intentionally for their reputation or remuneration concerns. Trueman (1994), proposing a model on analyst's forecasting behavior, shows that the earnings forecasts made by analysts do not necessarily contain their private information, and there is a tendency to announce forecasts similar to those made by other analysts to copy higher ability and for higher remuneration. In addition, herding would be occurred unintentionally due to their common education background, use of similar indicators in their analyses or similar stock characteristics employed with investment styles such as value, growth and momentum investing. Further, the theoretical models of Bikhchandani *et al.* (1992) and Banerjee (1992) argue that herding is a rational behavior when other investors have important information relating to one's decisions. Thus, following the others' trading patterns enables to infer such information.

On the other hand, since investors are bounded rational, their sentiment such as optimism, pessimism, fear and ambiguity can affect their investment decision-making. Thus, herding is likely to occur irrationally through such emotions triggered in response to events and conditions in financial markets, for example, information scarcity and asymmetry, extreme volatility or instability, fads and trends (Spyrou, 2013). As many previous studies show[3], investors are optimistic (pessimistic) in rising (falling) markets, hence, are more likely to follow the market trend disregarding the fundamentals. Similar to those of developed and emerging markets, the studies conducted for frontier markets reveal such herd tendencies in both up and down market days. However, the findings are mixed with respect to the asymmetry of herd formation between these up and down market movements. Arjoon and Bhatnagar (2017) on the Trinidad and Tobago Stock Exchange and Rahman *et al.* (2015) on the Saudi Stock Exchange find a stronger herding in the up-market direction, indicating the fact that investors are more inclined to herd when they are optimistic about market conditions. On the contrary, the findings of Economou (2016) on the stock exchanges of Nigeria and Morocco and Vo and Phan (2016) on the Vietnam stock market reveal that herding is stronger with investors' pessimistic mood during falling market days than their optimistic mood during rising market days. However, Guney *et al.* (2017) show that herding occurs irrespective of the direction of market movements in the African stock exchanges.

In addition, fear and ambiguity dominate among investors under uncertainty. Consequently, they may react to the uncertainty by herding others' trading patterns. Guney *et al.* (2017) show that herding is strongly present during high volatility days than low volatility days. The study of Balcilar *et al.* (2013) conducted for the Gulf Arab stock markets also suggests that high market volatility influences the formation of herd behavior. Further, the literature reveals that smaller stocks enhance the magnitude of herding due to the greater information uncertainty when trading them (Arjoon and Bhatnagar, 2017; Guney *et al.*, 2017). Hwang and Salmon (2004) and Liao *et al.* (2011) emphasize that emotion is a key driver of herding. Prechter (2001) also shows that sentiment leads investors to follow fads and trends, resulting to herd formation in financial markets. Furthermore, social environment, which is typically characterized by interactions, religious activities, social circles and social conventions, has an influence on herd formation. Hong *et al.* (2004) and Lu and Tang (2015) show how social interactions motivate less sophisticated investors to follow others' strategies, resulting to convergence of investment behavior to a social norm. Gavriilidis *et al.* (2016) find a stronger herd behavior during days of Ramadan than non-Ramadan days, which supports for the fact that social interaction and positive mood are determinants of herding in financial markets.

2.2 Evolution of herding

The evolutionary nature of behavioral biases is a research initiative emerged with the AMH of Lo (2004, 2005, 2012). The AMH assumes that market participants are neither perfectly rational nor perfectly irrational. Rather, their rationality is an evolving phenomenon, driven by market forces and their adaptability to market conditions. This evolutionary perspective hypothesizes that they are capable of adapting to market environment by learning about their biases from the reinforcements and the associated emotions experienced with their past behaviors. Thus, the level of rationality depends on the extent to which they are able to learn and select the right behavior for adapting to market conditions. Hence, given enough time and competitive market forces, the market participants with maladaptive behaviors are eliminated from the market population due to losses, and the market will eventually consist of those who adapt to its environment. Consequently, it can expected that behavioral biases decline and disappear over time at the aggregate market level.

In view of that, herd bias could occur with varying magnitude depending on the nature of market environment. In the process of investors' adapting to market conditions, it could evolve to negative herding and absence of herding statuses, as explained below.

2.2.1 Negative herding. The negative herd behavior, also known as "reverse herding" or "anti-herding", takes place when investors act against the market consensus by trading stocks based on views dominant among their subgroups, or at an extreme case, based on each of their own beliefs (Bohl *et al.*, 2017; Gębka and Wohar, 2013). Thus, negative herding symbolizes investors' increased individuality in decision-making (Galariotis *et al.*, 2016). Consequently, stocks are traded excessively based on diverse beliefs of the investors, leading to an increase of price dispersions above the level of rational pricing. Gębka and Wohar (2013) show that the negative herding arises due to phenomena such as investor overconfidence and panic selling induced by uncertain market conditions. In case of overconfidence, following raising market periods, investors tend to attribute high performance of their portfolios to their own skills in stock selection and other abilities rather than to the market conditions. Thus, they are likely to over rely on their own views while ignoring market signals when making subsequent investment decisions. This can result to a high risk-seeking behavior by buying risky stocks and selling low risk investments to greater level. In case of panic selling, during periods of high volatility and uncertainty, irrational fear dominates among investors. Consequently, they become more risk-averse and rebalance their portfolios to more secure positions by selling risky stocks and buying less risk investments to a greater extent. In these instances, stocks would be traded excessively, increasing the price dispersions above the rational level. The former instance leads to a rapid increase of market whereas the latter causes to a substantial market decline.

2.2.2 Absence of herding. This refers to a situation where market participants neither trade by following the market-wide price signals nor exhibit excessive trading as in case of negative herding. It indicates the fact that investor are mostly informed of stock fundamentals. Thus, the trading is based such information, but not merely following the observed actions of other investors or the market-wide price fluctuations. As a result, stocks tend to be traded in a way that results in price dispersions occurring at the rational level.

Certain studies in the literature support the absence of herding status at the aggregate market level. Nguyen (2018) and Yao *et al.* (2014) show that, after periods of significant herding, it declines and becomes absent due to the effectiveness of regulatory reforms in the respective markets. Choe *et al.* (1999) and Hwang and Salmon (2004) find a declining herd tendency following a financial crisis period, which indicates fact that the outbreak of a crisis as a turning point for herd evolution. Arjoon and Bhatnagar (2017) also reveal a strong tendency to herd during periods of high market stress and financial turmoil, which, however, disappears afterwards. They suggest that the regulatory reforms in the aftermath of the crisis to improve the informational environment produce a greater awareness of company fundamentals to investors, hence, lead to the absence of herding in the market.

Alternatively, considering the evolutionary nature of behavioral biases implied by the AMH, the absence of herding can be expected when investors learn the irrationality of herding and pursue the right behavior for adapting to market environment. As the AMH assumes, the learning occurs through the reinforcements and associated emotions experienced from their past behaviors. However, the extant literature casts some doubt on the validity of the reinforcement learning assumption in reducing behavioral biases. If this assumption is valid, a higher level of experience should result to a lower level of behavioral biases. However, previous studies reveal that the experienced investors are more exposed to behavioral biases than the inexperienced investors (Mishra and Metilda (2015), Baker *et al.* (2019) and references therein). In addition, concerning on the cognitive aging, Korniotis and Kumar (2011) argue that though the older investors have a greater investment knowledge through their experience, their aging impedes the application of their experiences to reduce behavioral biases. Hirshleifer (2015) also claim that reinforcement learning can bias the learning process as investors merely extrapolate their own past experiences, without appropriately reflecting on the experiences when learning. Further, Chiang *et al.* (2011) and Choi *et al.* (2009) find the evidence on the investors' tendency to over-extrapolate their past experiences when making decisions.

In view of above evidence, Shantha *et al.* (2018) propose a model of investor learning, which claims that past experiences do not merely result in learning, rather the self-reflection of such experiences facilitates to reduce behavioral biases in decision-making. Thus, the learning occurs when investors cognitively evaluate the validity of mental frames such as beliefs and assumptions underlying their past behaviors by reflecting on the associated experiences. This self-reflection process enables to revise biased mental frames so that future behavior is modified accordingly. Supporting this view, Shantha (2019) find that herd bias is not declined merely by past investment experiences. Rather, investors learn the irrationality of herding through the self-reflection of their experiences so that it is minimized depending on the extent to which they involve in this self-reflection process.

2.3 Previous studies on the Colombo Stock Exchange

There exists a limited number of studies and inconclusive evidence on herd bias in respect of the CSE. According to my best knowledge, there are only three published studies of the market-wide herding on the CSE. It was first examined by Sewwandi (2016) for the entire market and separately for up- and down-market days over the 2001-2015 period, using the Cross Sectional Absolute Deviation methodology suggested by Chang *et al.* (2000) (hereafter called as "CSAD model") with the OLS approach. The results show no evidence of herd behavior during this period. Then, Xiaofang and Shantha (2017) examined it for the 2007-2016 period by applying both the OLS and the QR approaches to the CSAD model. Their OLS findings, consistent with Sewwandi (2016), suggest absence of herding, whereas the results based on the QR procedure provide evidence to support herding in the market during the period. Afterwards, following the same methodology with the OLS approach, Xiaofang and Shantha (2018) reexamined it for the 2000-2016 period. According to their results, herding is strongly evident during the 2000-2008 period, whereas it is absent during the 2008-2016 period. Therefore, studying further about herd behavior on the CSE could provide more insight into these mixed empirical findings reported by those previous studies.

3. The investment environment of the Colombo Stock Exchange and its influence on herding

Currently, the CSE has 298 listed companies, covering 20 business sectors. The total market capitalization as of 31 March 2018 was LKR 3,032.7bn, representing about 22 per cent of the GDP. Similar to most of other frontier markets, the domestic investors presently dominate the CSE, which is about 85 per cent of the total number of shares traded and 96 per cent of the total number of trades executed during the last five years. Further, trading by retail investors represents a significant proportion of the stock trading, which is on average 80 per cent of total number of trades executed.

The CSE, as a pre-emerging market, is regularly exposed to certain risks that cause impediments to its functioning such as regulatory risk, governance risk, liquidity risk, trade execution risk, high vulnerability to economic and environmental shocks and dominance of noise trading. These risks could lead to unfavorable consequences in the market, for example, information asymmetry, insider trading, low transparency, price manipulation, significant mispricing and a few number of securities actively traded, which would discourage investor participation for investing and trading in the market. Consequently, such risks impair both the amount and quality of information incorporated into prices of securities, eventually rendering to a more ambiguous informational environment in the CSE. Accordingly, it is likely that the investors tend to herd for resolving this information uncertainty (Guney *et al.*, 2017).

The trading environment of the CSE was highly uncertain over the past few decades due to the impacts of economic crises and political instability of the country. The two-decade Civil War worsened the country's economy and political stability. During this period, the market experienced a lower trading volume, which resulted to a low level of liquidity and a slower growth rate in the market. However, since the end of the war in 2009, the market continued with a rapid growth, rising to a speculative bubble which crashed during the period from March 2011 to July 2012. Though the market started to regain its position afterwards, its trading environment has again become highly uncertain since the year 2015 due to the effects of political transitions and economic crisis of the country. Given such stressful market environment, it is also more probable that the investors disregard their own beliefs and are prone to imitate others' behaviors when making their trading decisions (Arjoon and Bhatnagar, 2017; Hwang and Salmon, 2004; Olsen, 2011).

4. Data

The sample period covers the trading days from April 3, 2000 to March 29, 2018, which consists of a total of 4,305 trading days. A long time window is selected to consider different market episodes of the CSE in the analysis, as shown in Figure 1 and explained below. The time duration from April 2000 to March 2009 represents the period during which the CSE was affected by the political instability of the country as a consequence of the Civil War. Since the end of it, the market showed a rapid growth and was built up to a speculative bubble which crashed during the period from March 2011 to July 2012. The time period subsequent to the crash is split into two sub-periods based on the date of the presidential election, January 8, 2015 as the cut-off point. During the period after the presidential election, the market experienced a slower growth mainly due to the effects of the political instability and the economic crisis of the country. It is expected that such a long time span consisting of different events and conditions affecting the market, provides an appropriate ground for the examination of the evolutionary nature of herding.

The data set includes daily closing prices[4] of all listed common stocks, which is available in the Data Library (CD ROM) of the CSE. Consistent with the previous studies[5], both the active and the suspended/delisted stocks during the sample period were included in the sample to alleviate possible survivorship bias affecting the results. A stock's price observations were included in the data set only for the days it was traded so that non-trading or thin trading would have no effects to the results. Accordingly, the final data set includes a total of 321 stocks with 746,518 daily price observations.

5. Methodology

Since this study covers the examination of the evolutionary nature of herding at the market level, a model to detect market-wide herding is employed here. Christie and Huang (1995) and Chang *et al.* (2000) propose respectively the cross-sectional standard deviation (CSSD) model and the CSAD model for detecting the market-wide herd behavior. As the CSSD model examines herding occurred at extreme market movements, it requires defining the extreme lower and upper tails of the return distribution. Consequently, its results are biased towards the definition of the extreme returns and it ignores such behavior occurred during stable market days. Further, it does not account for the nonlinearities of the return in the presence of herding and is sensitive to outliers in data. On the other hand, the CSAD model, as provided by equation (1) below, overcomes these weaknesses[6]. Therefore, it has been the most extensively used model in the market-wide herding studies so far.

$$CSAD_t = \propto + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t \tag{1}$$

In equation (1), R_{mt} and $|R_{mt}|$ stand for the equally weighted cross-sectional average return of all stocks (market portfolio) on day t and its absolute value respectively. $CSAD_t$ represents the equally weighted cross-sectional absolute deviation of stock return on day t, calculated according to the equation (2).

$$CSAD_t = (1/N) \sum_{i=1}^{N} |R_{it} - R_{mt}| \tag{2}$$

In equation (2), R_{it} denotes return of stock i on day t, determined as the first logarithmic difference of daily closing prices, and N is the number of stocks in the market portfolio on day t.

5.1 Test of herding and negative herding

When the market participants do not herd, stocks are expected to be traded based on their diverse beliefs about stock fundamentals. Thus, as the Capital Assets Pricing Model implies, the cross sectional absolute deviation of return is a linear and increasing function of the market return. This indicates that the relationship between $CSAD_t$ and R_{mt} is linear and positive, resulting to a significantly positive value for γ_1 and an insignificant value for γ_2 in equation (1).

In the event of herding, since stocks are traded based on information emerged from the market-wide price fluctuations, the stock returns tend to get distributed around the market return, thereby, declining the $CSAD_t$. Accordingly, when herding occurs, the relationship between $CSAD_t$ and R_{mt} becomes negative and non-linear, leading to a significantly negative value for γ_2 in equation (1).

Conversely, negative herding occurs when investors trade stocks excessively by acting against the market-wide price fluctuations. It results to an increase of price dispersions above the rational level, which is reflected by a significant positive value of γ_2 in equation (1).

5.2 Test of asymmetric herding effects between up and down market movements

The empirical analysis is further carried out to test whether herding effects are significantly different between the periods of positive market returns (up-market days) and the periods of negative market returns (down-market days). Following the approach proposed by Chiang and Zheng (2010), the equation (3) depicts the extended CSAD model to detect herding asymmetry conditional on the market return.

$$CSAD_t = \propto + \gamma_1 D_t^{up}|R_{mt}| + \gamma_2 D_t^{up} R_{mt}^2 + \gamma_3\left(1 - D_t^{up}\right)|R_{mt}| + \gamma_4\left(1 - D_t^{up}\right)R_{mt}^2 + \varepsilon_t \tag{3}$$

In equation (3), D_t^{up} stands for the dummy variable taking the value of 1 for up-market days and zero value for down-market days. Market days are considered to be up- (down-) market when $R_{mt} > 0$ ($R_{mt} < 0$).The Wald test is performed to examine herding asymmetry between these market movements.

5.3 Ordinary least square and quantile regression approaches for estimating the cross-sectional absolute deviation model

The regression coefficients of the equations (1) and (3) are customary estimated by applying the OLS approach. The OLS approach requires the parametric assumptions on its error distribution to be satisfied. It is also not an appropriate method when non-linearity exists in the equation and outliers are present in the data[7]. On the other hand, the QR[8] is a semi-parametric regression approach so that it does not necessitate fulfilling the parametric assumptions and is less sensitive to outliers in the data[9]. Hence, the QR is considered to be a more robust method than the OLS regression. In addition, the QR provides a complete picture of how the regression estimates vary over the entire distribution of the dependent variable. Thus, it facilitates to make inferences by examining herding over the entire distribution of $CSAD_t$, especially its magnitude under the extreme market movements. Accordingly, herding estimates are obtained using both the OLS and the QR methods. Equations (4) and (5) represent the QR models for the examination of herding for aggregate market and up-and down-market days respectively[10].

$$Q_\tau(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau}|R_{mt}| + \gamma_{2,\tau}R_{mt}^2 \tag{4}$$

$$Q_\tau(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau} D_t^{up}|R_{mt}| + \gamma_{2,\tau} D_t^{up} R_{mt}^2 + \gamma_{3,\tau}\left(1 - D_t^{up}\right)|R_{mt}| + \gamma_{4,\tau}\left(1 - D_t^{up}\right) R_{mt}^2 \quad (5)$$

where τ represents for quantiles, $\tau \in \{0, \ldots, 1\}$.

The bootstrap technique[11] is employed with the xy-pair design[12] and for 600 replications[13] for computing the confidence intervals of the regression quantiles.

5.4 Hypotheses for examining the evolution of herding

The evolutionary nature of herding is examined by splitting the total sample period into different sub-periods, as shown in Figure 1. Table I shows the results of the Chow's break point test to validate the cut-off points for these sub-periods.

First, the total sample period is equally divided into two sub-periods, consisting of 9 years each. The first nine-year period, covering from April 2000 to March 2009, represents a period during which the country was politically unstable as a result of the Civil War. The high level of uncertainty during this time period considerably affected the flow of investments into and the trading activities of the market, which consequence to a lower liquidity and a slower market growth rate, as reflected by Figure 1. Thus, it can be expected that, in additions to the risks that the CSE is commonly exposed as a frontier market, the market uncertainties caused by the war, in particular, strengthen herd tendency during the 2000-2009 period, as given by the *H1*.

H1. Investors are prone to herding irrespective of the direction of market movement during the 2000-2009 period so that $\gamma_2 < 0$ in equations (1) and (4), and $\gamma_2 < 0$ and $\gamma_4 < 0$ in equations (3) and (5).

The second 9-year period, spanning from April 2009 to March 2018, is examined by separating into the market bubble period (April 2009 to February 2011), the market crash period (March 2011 to July 2012), and the post-crash period (August 2012 to March 2018). The post-crash period is further split into two periods, namely the periods before and after the presidential election, based on the date of the election (January 8, 2015) as the cut-off point. Accordingly, the second 9-year period consists of four sub-periods, as depicted in Figure 1. The following hypotheses are examined for these sub-periods.

H2. Investors follow the positive price signals emitted in the market since the end of the Civil War in favor of their beliefs about stock fundamentals. Thus, herding would

Sub-periods	Break date	*F*-statistic	*p*-value
Periods before and after the Civil War (April 2000 to March 2018)	1/4/2009	441.861	0.000
Market bubble and crash periods (April 2009 to July 2012)	1/3/2011	18.304	0.000
Periods before and after the presidential election (August 2012 to March 2018)	8/1/2015	421.911	0.000

Notes: This table reports the results relating to the Chow's break point test for examining the validity of the cut-off points used in dividing the total sample period into different sub-periods. The significance of *F*-statistic rejects the null hypothesis that there is no break at the specified break point

Table I.
Results of the chow's break point test

occur in the up-market direction during the bubble period so that $\gamma_2 < 0$ in equations (1) and (4), and $\gamma_2 < 0$ and $\gamma_4 = 0$ in equations (3) and (5).

H3. Investors are fear of the uncertainty of the inflated stock prices that occurred during the bubble period. Thus, they act against the market consensus by rebalancing their portfolios to safe positions by selling risky stocks (increased individuality in decision-making). Thus, negative herding would occur in the down-market direction during the market crash period so that $\gamma_2 > 0$ in equations (1) and (4), and $\gamma_2 = 0$ and $\gamma_4 > 0$ in equations (3) and (5).

H4. Investors learn from the losses occurred due to the irrationality of herding and negative herding. Consequently, they tend to get away from such behavior during the period after the market crash, despite the fact that herd motives such as economic and political uncertainties and high market volatility strongly appear during this post-crash period. Accordingly, $\gamma_2 = 0$ in equations (1) and (4), and $\gamma_2 = 0$ and $\gamma_4 = 0$ in equations (3) and (5) during the periods before and after the presidential election.

Table II shows a summary of statistics of $CSAD_t$ and R_{mt} for the entire sample period and the sub-periods. Except for the market crash period and the period after the election, the mean value of R_{mt} is consistently positive. It takes the highest value during the bubble period, which reflects strong positive price signals emitting from the market since the end of the war. The standard deviation, which reveals the magnitude of the volatility, of $CSAD_t$ is

Period covered		Mean	SD	Skewness	Jarque–Bera statistic	ADF statistic
Panel A: Total Sample						
	$CSAD_t$	1.036	0.409	2.072	11,208.67***	−6.261***
	R_{mt}	0.053	0.713	0.302	56,297.92***	−45.604***
Panel B: 9-year sub-periods						
2000-2009	$CSAD_t$	1.160	0.475	1.858	3,110.50***	−11.204***
	R_{mt}	0.065	0.873	0.231	18,030.52***	−33.088***
2009-2018	$CSAD_t$	0.911	0.278	1.328	2,403.99***	−7.238***
	R_{mt}	0.041	0.504	0.368	5,962.32***	−22.797***
Panel C: Analysis of the 2009-2018 sub-period						
Bubble period	$CSAD_t$	0.999	0.248	1.132	195.47***	−4.597***
	R_{mt}	0.189	0.561	−0.172	251.85***	−18.228***
Crash period	$CSAD_t$	1.080	0.289	1.842	824.79***	−6.298***
	R_{mt}	−0.059	0.766	0.678	624.59***	−15.496***
Before-election	$CSAD_t$	0.981	0.238	0.966	109.74***	−7.670***
	R_{mt}	0.046	0.433	0.255	67.36***	−9.140***
After-election	$CSAD_t$	0.728	0.214	3.156	19751.99***	−6.596***
	R_{mt}	−0.009	0.318	0.120	615.18***	−10.717***

Notes: This table reports statistical properties of the cross-sectional absolute deviation of returns ($CSAD_t$) and the market return (R_{mt}) series for the sample period from 3/4/2000 to 29/3/2018. Each sub-period given in panel B begins on the April 1 and ends on the March 31 of the given years. Panel C shows the analysis of the 2009-2018 period by split into the market bubble period (April, 2009 to February, 2011), the market crash period (March, 2011 to July, 2012), and the post-crash period (August, 2012 to March, 2018) which is further separated into the periods before and after the presidential election using the date of the election (January 8, 2015) as the cut-off point. The statistical significance at the 1, 5 and 10 per cent levels are represented by ***, ** and * respectively

Table II.
Descriptive statistics

lower than that of R_{mt} throughout the entire sample period. In addition, the volatility of the series of $CSAD_t$ and R_{mt} are higher during the first half of the sample period than those of the second half. The Augmented Dickey-Fuller (ADF) test statistic rejects the null hypothesis of unit root for both of these variable series, indicating their stationary over the sample period. However, Jarque-Bera statistics show that $CSAD_t$ and R_{mt} series are non-normal. They are skewed to the right, as indicated by the positive skewness statistics. Since the non-normality of the variables may affect the validity of the OLS results, the QR analysis is important here to provide robust evidence to examine the hypotheses.

6. Analysis of results and discussion

The empirical results are reported in the following order. First, the results of the aggregate market are discussed in relation to the total sample period and the sub-periods. Then, those relating to the up and down market days are presented with the evidence on asymmetric herding effects conditional on these market movements. After that, the results are compared over different market periods of the CSE such as period of uncertain market conditions due to the Civil War, market bubble and crash periods and period subsequent to the crash to examine evolution of herding over these market periods. The coefficients, γ_1 in equations (1) and (4), and γ_1 and γ_3 in equations (3) and (5) are significantly positive in both total sample and sub-sample periods' tests, supporting the assumption on the positive relationship between $CSAD_t$ and $|R_{mt}|$.

6.1 Herd behavior at the aggregate market level

Tables III and V present respectively the OLS estimates [estimating equation (1)] and the QR estimates [estimating equation (4)] for examining herd behavior at the aggregate market level. A significantly negative (positive) value of γ_2 indicates herd behavior (negative herding). With respect to the OLS estimates, γ_2 is significantly negative for the total sample

Period covered	$\propto$	γ_1	γ_2	Adjusted R^2
Panel A: Total sample				
	0.765 (59.494)***	0.641 (17.189)***	−0.044 (−4.188)***	0.471
Panel B: 9-year sub-periods				
2000-2009	0.825 (46.552)***	0.651 (13.957)***	−0.046 (−3.828)***	0.481
2009-2018	0.738 (50.260)***	0.536 (11.155)***	−0.048 (−1.590)	0.357
Panel C: Analysis of the 2009-2018 sub-period				
Bubble period	0.839 (33.936)***	0.446 (6.569)***	−0.106 (−3.077)***	0.191
Crash period	0.945 (41.341)***	0.205 (4.320)***	0.048 (3.900)***	0.426
Before-election	0.832 (46.582)***	0.494 (6.632)***	−0.070 (−1.070)	0.244
After-election	0.568 (40.491)***	0.755 (10.839)***	−0.084 (−1.554)	0.504

Notes: This table reports the OLS regression results for the aggregate market, as estimated from equation (1), over the sample period from 3/4/2000 to 29/3/2018. Each sub-period given in panel B begins on the April 1 and ends on the March 31 of the given years. Panel C shows the analysis results of the 2009-2018 period by split into the market bubble period (April, 2009 to February, 2011), the market crash period (March, 2011 to July, 2012), and the post-crash period (August, 2012 to March, 2018) which is further separated into the periods before and after the presidential election based on the date of the election (January 8, 2015) as the cut-off point. The t-statistics are computed based on the Newey and West (1987) test for heteroskedasticity and autocorrelation consistent standard errors and given in parentheses. The statistical significance at the 1, 5 and 10 per cent levels are represented by ***, ** and * respectively

Table III. OLS Estimates of herding at the aggregate market level period and the 2000-2009 sub-period, as shown in panel A and B of Table III. However, it turns into be insignificant during the subsequent period from 2009 to 2018. The QR results are consistent with these OLS estimates. The coefficient γ_2 is significantly negative at all quantile intervals of the total sample period and the 2000-2009 sub-period, as reported in Panel A and B of Table V. However, in relation to the second half of the sample period (2009-2018), γ_2 is significantly negative only at the 0.05 and 0.25 quantile intervals. Thus, according to both the OLS and the QR evidence, herd behavior is strongly evident during the first half of the sample period, which, however, becomes mostly insignificant during the second half. Notably, during the first half, the coefficient γ_2 seems to increase from the median quantile (0.50) to the extreme lower (0.05) and the extreme upper (0.95) quantile intervals, indicating a strong tendency to herd during the extreme market conditions.

These results are not consistent with those found by Sewwandi (2016) and Xiaofang and Shantha (2017) on the CSE. By considering all listed firms, Sewwandi (2016) found no evidence of herding for the period from 2001 to 2015. Subsequently, Xiaofang and Shantha (2017) examined whether investors tend to herd when trading stocks of non-financial firms listed during the period from 2007 to 2016. Their OLS results are consistent with those of the current study for the 2009-2018 period, which reveal no evidence of herd behavior. However, their QR results, contrary to those of the current study, show the presence of herd behavior from the extreme lower to the middle quantile intervals and reverse herding from the middle to the extreme upper quantile intervals[14].

6.2 Herd behavior in up and down market days

Tables IV and VI contain respectively the OLS estimates [estimating equation (3)] and the QR estimates [estimating equation (5)] for examining herd behavior in periods of up and down market movements. Significantly negative (positive) values of the coefficients γ_2 and γ_4 reflect herd behavior (negative herding) in up- and down-market days respectively. As given in Table IV, the OLS estimates indicate herd behavior in both up- and down-market days for the total sample period and the first half of the sample period (2000-2009). Further, it appears to have occurred irrespective of the direction of the market movements since the findings reveal an absence of herd asymmetry between up- and down-market days during this period (as reflected by insignificant Wald test statistics). Nevertheless, the estimates of the second half of the sample period (2009-2018) show herd behavior only for up-market days.

Consistent with the OLS evidence, the QR estimates (Table VI) show herding in both up- and down-market days at all quantile intervals of the total sample period (panel A) and the first half period (panel B) with no strong evidence of herd asymmetry between these up- and down-market movements. Further, supporting the QR estimates of the aggregate market, Panel B of Table VI reveals increased herd behavior from the median quantile to the extreme upper (0.95) and the extreme lower (0.05) quantile intervals of both up- and down-market days, indicating a stronger tendency to herd during the extreme market conditions over the 2000-2009 period. However, when the results relating to the second half of the sample period are concerned, consistent with the OLS estimates, herding is mostly absent during down-market days, as shown in Panel B of Table VI.

Accordingly, both the OLS and the QR results reveal that investors tend to herd strongly in both rising and falling market days over the 2000-2009 period, and get away themselves from such irrational behavior mostly during the falling market days of the subsequent 2009-2018 period. These findings are considerably different from those of the previous studies conducted by Sewwandi (2016) and Xiaofang and Shantha (2017) on the CSE as follows. Applying the OLS procedure, Sewwandi (2016) and Xiaofang and Shantha (2017) found no

Table IV. OLS Estimates of herding conditional on market performance

Period covered	$\propto$	Up-market days γ_1	γ_2	Down-market days γ_3	γ_4	Adjusted R^2	Wald test $\gamma_2 - \gamma_4 = 0$
Panel A: Total sample							
	0.764 (62.840)***	0.685 (21.293)***	−0.043 (−5.245)***	0.597 (14.630)***	−0.049 (−5.784)***	0.478	0.006 [0.343]
Panel B: 9-year sub-periods							
2000-2009	0.819 (49.878)***	0.696 (17.993)***	−0.044 (−5.489)***	0.632 (12.319)***	−0.059 (−5.603)***	0.490	0.016 [2.036]
2009-2018	0.742 (50.916)***	0.619 (12.291)***	−0.078 (−2.442)**	0.405 (7.962)***	−0.003 (−0.097)	0.371	−0.075 [10.476]***
Panel C: Analysis of the 2009-2018 sub-period							
Bubble period	0.854 (34.619)***	0.522 (7.639)***	−0.125 (−3.213)***	0.071 (0.848)	0.021 (0.634)	0.284	−0.146 [14.228]***
Crash period	0.951 (41.042)***	0.278 (5.163)***	0.018 (1.285)	0.124 (2.233)**	0.081 (5.833)***	0.436	−0.063 [14.249]***
Before-election	0.828 (46.096)***	0.523 (7.169)***	−0.064 (−1.124)	0.526 (4.882)***	−0.163 (−1.305)	0.247	0.100 [0.601]
After-election	0.572 (40.346)***	0.873 (11.377)***	−0.130 (−1.400)	0.618 (7.731)***	−0.033 (−0.584)	0.522	−0.097 [1.280]

Notes: This table reports the OLS regression results for up and down market days, as estimated from equation (3), over the sample period from 3/4/2000 to 29/3/2018. Each sub-period given in panel B begins on the April 1 and ends on the March 31 of the given years. Panel C shows the analysis results of the 2009-2018 period by split into the market bubble period (April, 2009 to February, 2011), the market crash period (March, 2011 to July, 2012), and the post-crash period (August, 2012 to March, 2018) which is further separated into the periods before and after the presidential election based on the date of the election (January 8, 2015) as the cut-off point. The *t*-statistics are computed based on the Newey and West (1987) test for heteroskedasticity and autocorrelation consistent standard errors and given in parentheses. Herding asymmetry between up and down market days is examined by the Wald test, based on the null hypothesis of γ_2 - γ_4=0 and the Chi-square statistics shown in square brackets. The statistical significance at the 1, 5 and 10 per cent levels are represented by ***, ** and * respectively

Table V.
QR Estimates of herding at the aggregate market level

Quantile	θ_τ	γ_1	γ_2	Adjusted R^2
Panel A: Total Sample				
0.05	0.468 (54.533)***	0.564 (15.570)***	−0.090 (-3.902)***	0.231
0.25	0.627 (84.371)***	0.528 (22.703)***	−0.044 (-4.383)***	0.235
0.50	0.732 (88.572)***	0.603 (19.368)***	−0.041 (-3.227)***	0.254
0.75	0.879 (85.779)***	0.666 (18.990)***	−0.035 (-2.631)***	0.282
0.95	1.092 (74.171)***	1.159 (16.173)***	−0.088 (-2.847)***	0.379
Panel B: 9-year sub-periods; 2000- 2009 sub-period				
0.05	0.505 (30.678)***	0.554 (11.426)***	−0.077 (-3.356)***	0.238
0.25	0.686 (57.077)***	0.492 (15.261)***	−0.034 (-3.159)***	0.246
0.50	0.798 (64.575)***	0.594 (16.842)***	−0.041 (-3.062)***	0.273
0.75	0.942 (52.218)***	0.700 (12.204)***	−0.039 (-2.167)**	0.305
0.95	1.152 (43.262)***	1.210 (12.415)***	−0.093 (-2.493)**	0.393
2009- 2018 sub-period				
0.05	0.446 (40.990)***	0.632 (12.595)***	−0.186 (-4.481)***	0.223
0.25	0.582 (56.099)***	0.618 (11.824)***	−0.154 (-3.814)***	0.176
0.50	0.693 (62.781)***	0.570 (9.526)***	−0.065 (-1.239)	0.203
0.75	0.839 (56.110)***	0.595 (9.450)***	−0.039 (-1.010)	0.195
0.95	1.104 (49.244)***	0.603 (7.230)***	−0.046 (-1.260)	0.211

Notes: This table reports the QR results for the aggregate market, as estimated from equation (4), over the sample period from 3/4/2000 to 29/3/2018. Each sub-period given in panel B begins on the 1st April and ends on the 31st March of the given years. The t-statistics are computed based on bootstrap standard errors and given in parentheses. The statistical significance at the 1%, 5% and 10% levels are represented by ***, ** and * respectively

Table VI. QR Estimates of herding conditional on market performance

Quantile	θ_τ	Up-market days γ_1	Up-market days γ_2	Down-market days γ_3	Down-market days γ_4	Adjusted R^2	Wald Test $\gamma_2 - \gamma_4 = 0$
Panel A: Total sample period							
0.05	0.469 (50.649)***	0.678 (14.252)***	−0.134 (−4.024)***	0.492 (13.597)***	−0.067 (−2.974)***	0.245	−0.067 [3.651]
0.25	0.628 (90.063)***	0.607 (14.989)***	−0.055 (−2.012)**	0.426 (20.601)***	−0.023 (−2.461)**	0.249	−0.032 [2.024]
0.50	0.739 (88.942)***	0.651 (19.264)***	−0.041 (−2.278)**	0.467 (18.385)***	−0.025 (−2.581)***	0.265	−0.016 [0.793]
0.75	0.874 (87.572)***	0.734 (17.958)***	−0.042 (−2.572)***	0.606 (15.573)***	−0.044 (−4.386)***	0.287	0.002 [0.010]
0.95	1.090 (66.668)***	1.160 (10.471)***	−0.088 (−1.969)**	1.269 (10.224)***	−0.150 (−2.693)***	0.379	0.063 [0.910]
Panel B: 9-year sub-periods							
2000-2009 sub-period							
0.05	0.509 (30.621)***	0.628 (10.487)***	−0.098 (−3.067)***	0.496 (10.746)***	−0.063 (−2.855)***	0.250	−0.035 [1.157]
0.25	0.679 (62.342)***	0.604 (13.151)***	−0.054 (−2.244)**	0.427 (15.987)***	−0.026 (−2.710)***	0.262	−0.028 [1.064]
0.50	0.807 (70.121)***	0.620 (16.808)***	−0.031 (−1.740)*	0.476 (13.603)***	−0.028 (−2.622)***	0.283	−0.002 [0.013]
0.75	0.931 (58.776)***	0.773 (15.848)***	−0.046 (−2.123)**	0.648 (11.806)***	−0.052 (−4.215)***	0.312	0.006 [0.073]
0.95	1.147 (49.163)***	1.158 (12.684)***	−0.088 (−2.210)**	1.473 (12.763)***	−0.183 (−5.318)***	0.401	0.095 [3.315]*
2009-2018 sub-period							
0.05	0.443 (49.062)***	0.799 (9.548)***	−0.268 (−3.169)***	0.566 (10.933)***	−0.143 (−3.418)***	0.236	−0.125 [2.720]*
0.25	0.583 (56.188)***	0.750 (13.543)***	−0.206 (−4.509)***	0.484 (10.085)***	−0.106 (−2.623)***	0.219	−0.100 [3.359]*
0.50	0.702 (60.012)***	0.660 (10.133)***	−0.108 (−1.780)*	0.405 (5.238)***	−0.005 (−0.071)	0.216	−0.103 [1.631]
0.75	0.850 (58.052)***	0.671 (9.827)***	−0.095 (−1.948)*	0.370 (5.120)***	0.024 (0.425)	0.206	−0.119 [3.411]*
0.95	1.110 (48.876)***	0.592 (6.297)***	−0.053 (−0.996)	0.545 (4.194)***	0.042 (0.280)	0.211	−0.095 [0.375]

Notes: This table reports the QR results for up and down market days, estimated from equation (5), over the sample period from 3/4/2000 to 29/3/2018. Each sub-period given in panel B begins on the April 1 and ends on the March 31 of the given years. The *t*-statistics are computed based on bootstrap standard errors and given in parentheses. Herding asymmetry between up and down market days is examined by the Wald test, based on the null hypothesis of γ_2 - γ_4=0 and the Chi-square statistics shown in square brackets. The statistical significance at the 1, 5 and 10 per cent levels are represented by ***, ** and * respectively evidence of herding in both up and down market days. The QR results of Xiaofang and Shantha (2017) reveal both herding and negative herding during up- and down-market days over the period from 2007 to 2016. In addition, the absence of herd asymmetry between up and down market days during the 2000-2009 period indicates that herding occurs independently from the direction of the market movement (Bekiros *et al.*, 2017; Klein, 2013).

6.3 The evolution of herd behavior over time under different market conditions

The evolutionary nature of herd behavior is examined by comparing the evidence over time under different market conditions of the CSE. The empirical results, as discussed in sections 6.1 and 6.2, reveal strong evidence of herd formation irrespective of the direction of the market movement during the first 9 years of the sample period (2000-2009). During this period, the country was politically unstable due to the Civil War, which impacted on trading and investments of the CSE. As Figure 1 exhibits, the market experienced a slower growth during this period since the uncertainties caused by the Civil War led to low trading volume and low liquidity in the market. Consequently, the investors might have disregarded stock fundaments and involved in herding towards more liquid stocks to ensure a higher chance of getting their orders executed in the market. Therefore, the evidence supports the *H1*, indicating that market uncertainty caused by the political instability induce investors to herd during the 2000-2009 period.

Then, the second half of the sample period (2009-2018) characterizes uncertain market episodes such as the market bubble, subsequent crash and the post-crash period affected by political and economic crises of the country. Though the literature suggests that uncertainty and high market volatility are motives for either herding or negative herding, the estimates given in panel B of Tables III, IV, V, and VI provide no strong support to this prediction. During the 2009-2018 period, while there is no evidence of negative herding, herding appears to be more towards the up-market direction, however, less intensely when compared to the 2000-2009 period.

A better picture of herd behavior during the 2009-2018 period can be gained when the estimates obtained separately for the market bubble, the crash and the post-crash sub-periods, as shown in Tables III, IV and VII, are considered in the analysis. They indicate changes in the directionality of herding between the bubble and the crash periods. Both the OLS and the QR estimates at the aggregate market level, as given in panel C of Tables III and VII, reveal strong evidence of herd formation during the bubble period (as indicated by significantly negative γ_2), whereas negative herding during the crash period (as indicated by significantly positive γ_2). In addition, panel C of Table IV shows that herd formation occurs during up-market days of the bubble period, whereas negative herding appears during down-market days of the crash period. Accordingly, the evidence supports the *H2*, indicating the investors' tendency to ignore their own views and trade stocks in favor of the positive price signals emanated in the market from the end of the Civil War, which resulted to a speculative bubble in the market (Bekiros *et al.*, 2017). Further, the evidence on negative herding during the crash period supports the *H3*, revealing the increased individuality in decision-making of the investors. Thus, during the crash period, investors would have relied more on their individual views about the uncertainty of inflated stock prices during the bubble period and resort to panic selling for rebalancing their portfolios to more secure positions (Gębka and Wohar, 2013). This panic selling caused to a declining market, eventually leading to the market crash.

Herding during the bubble period, as discussed above, can be attributed to the effects of investors' conservatism and representativeness biases and momentum trading. Lam *et al.* (2010, 2012) demonstrate that investors are affected by conservatism and representativeness

Quantile (%)	$\theta\tau$	γ_1	γ_2	Adjusted R^2
Panel A: Market Bubble period (April 1, 2009 to February 28, 2011)				
5	0.596 (26.029)***	0.314 (4.063)***	−0.068 (−1.556)	0.112
25	0.713 (52.459)***	0.348 (8.002)***	−0.074 (−3.071)***	0.115
50	0.804 (36.603)***	0.486 (6.333)***	−0.138 (−3.233)***	0.100
75	0.937 (29.175)***	0.534 (5.262)***	−0.136 (−2.215)**	0.098
95	1.206 (16.409)***	0.457 (1.878)*	−0.068 (−0.352)	0.108
Panel B: Market Crash period (March 1, 2011 to July 31, 2012)				
5	0.696 (28.161)***	0.076 (1.578)	0.087 (4.312)***	0.129
25	0.834 (32.243)***	0.090 (1.556)	0.076 (3.110)***	0.138
50	0.935 (39.551)***	0.189 (3.120)***	0.048 (2.080)**	0.171
75	1.069 (37.409)***	0.216 (2.525)**	0.048 (1.638)	0.219
95	1.207 (21.103)***	0.433 (2.734)***	−0.011 (−0.217)	0.364
Panel C: Post-crash Period - before the election (August 1, 2012 to January 8, 2015)				
5	0.608 (30.508)***	0.383 (3.965)***	−0.093 (−1.046)	0.114
25	0.698 (54.066)***	0.483 (6.088)***	−0.087 (−0.962)	0.142
50	0.793 (42.598)***	0.456 (4.824)***	−0.051 (−0.541)	0.144
75	0.902 (34.076)***	0.676 (5.666)***	−0.110 (−0.981)	0.139
95	1.204 (20.602)***	0.645 (2.920)***	−0.165 (−0.873)	0.120
Panel D: Post-crash Period- after the election (January 9, 2015 to March 31, 2018)				
5	0.393 (33.538)***	0.719 (8.302)***	−0.186 (−1.643)	0.244
25	0.488 (50.188)***	0.723 (10.755)***	−0.136 (−1.916)*	0.264
50	0.572 (59.983)***	0.720 (11.434)***	−0.109 (−1.500)	0.282
75	0.648 (70.177)***	0.715 (9.248)***	−0.067 (−0.728)	0.329
95	0.806 (16.882)***	0.347 (0.728)	0.718 (0.708)	0.394

Notea: This table reports the QR results, as estimated from equation (4), for the market bubble period, the market crash period and the post-crash period which is further split into the periods before and after the presidential election based on the date of the election (January 8, 2015) as the cut-off point. The *t*-statistics are computed based on bootstrap standard errors and given in parentheses. The statistical significance at the 1, 5 and 10 per cent levels are represented by ***, ** and * respectively

Table VII. QR Estimates of herding for the market bubble, the crash and the post-crash periods

biases at the same time. Accordingly, after the Civil War, investors are optimistic about the country's economy and political stability. However, their conservatism leads to slow updating of their beliefs, thus, tends to underreact to this structural change. As a consequence, momentum trading builds up in the market to profit from this under-reaction, resulting to excessive trading in the direction of this new information. Their representativeness bias causes for continuing this herd formation over the long-term, which leads to overreaction of prices to that structural change, forming a speculative bubble in the CSE. Then, subsequent price reversals result to burst of the bubble. Guo *et al.* (2017) show that such short-term momentum, long-term overreaction and reversal anomalies persist during periods of financial crisis. In view of that, herd behavior appears to be a reason for the crisis period of the CSE.

Notably, the evidence indicates the absence of herding subsequent to the market crash. The OLS estimates given in Panel C of Tables III and IV and the QR estimates given in Panel C and D of Table VII consistently show that both herding and negative herding are completely absent after the market crash (during both before and after the presidential election) even though herd motives such as market uncertainties caused by economic and political instability of the country strongly appear during this period. The previous studies[15] suggest regulatory reforms in the aftermath of a crisis as a reason for the absence of herding. However, there were no significant regulatory reforms in the CSE during this post-crash period. Hence, the absence of herding could be attributed to the evolutionary nature of behavioral biases, as predicted by the AMH. It implies that investors may have learned from their losses due to their irrational herding and negative herding, and adapted to a more rational behavior over time. The study conducted by Shantha (2019) on the CSE shows the evidence in support of this learning behavior at the individual investor level. Therefore, with the consideration of these empirical results, there is a strong evidence to confirm the *H4*.

7. Conclusion and implications

The aim of this study is to examine the evolution of herd behavior in a frontier stock market, the CSE of Sri Lanka. The findings, based on both the OLS and the QR procedures, reveal a strong herd tendency at the aggregate market level and up and down market days during the first half of the sample period (2000-2009). However, there is no evidence to support herd asymmetry between up and down market days. In addition, the magnitude of herding appears to increase during the days of the extreme market movements over this period. Accordingly, it is evident that the investors involved in herding irrespective of the direction of the market movement, however, more strongly at the extreme market conditions in the 2000-2009 period. During this first-half period, the market was highly uncertain as a consequence of the effect of the political instability of the country due to the Civil War. Hence, the results support for the general prediction that market uncertainties induce investors to imitate others' behaviors, while disregarding their own beliefs and information when trading stocks.

Contrary to the first half of the sample period, the results of the second half (2009-2018) reveal significant changes to herding pattern over different market episodes. On one hand, herding is evident during up-market days of the bubble period, whereas negative herding during down-market days when the bubble's burst occurred in the market. Thus, the results support the findings of the previous studies which indicate that herding causes unfavorable effects to financial markets such as bubbles and crashes (Spyrou, 2013). On the other hand, either herding or negative herding is not consistently evident during the period after the market crash, despite its motives, especially, market uncertainties resulting from the political instability and the economic crisis of the country occurred during that period. Accordingly, the findings support for the evolutionary nature of behavioral biases, as predicted by the AMH. Based on this evolutionary perspective and the findings of Shantha (2019), the absence of herding during the period after the market crash implies the investors' learning about the irrationality of herding and negative herding from their financial losses and associated psychological shocks such as panic and frustration experienced during the previous market periods. Consequently, they inclined to get away from such irrational behaviors subsequently.

Therefore, consistent with Bekiros *et al.* (2017), Klein (2013), Zhou and Anderson (2013) and Clements *et al.* (2017), herding is a dynamic phenomenon in a financial market. Hence, it is likely to evolve over time with period-specific characteristics of a market. As the AMH assumes, it could decline and disappear over time through the competition and adaptation of market participants' behaviors to market environment. Further, the evidence on the evolutionary nature of herding can be used as an explanation for the mix empirical findings on herding, as reported by the previous studies on the CSE (Sewwandi, 2016; Xiaofang and Shantha, 2017, 2018).

8. Limitations and future research directions

This paper provides insights on the evolutionary nature of herding at the aggregate market level, as a novel attempt for contributing the herding literature. Despite the selection of an appropriate market setting with a suitable study approach, the contribution of this paper is limited in respect of the following. First, the current literature demonstrates a set of market characteristics as determinants of herding, for example, stock size, trading volume, volatility, industry types and market integration (Spyrou, 2013). Herd evolution could also be a function of these factors. For instance, it would be significantly different between small vs large stocks, high trading volume days vs low trading volume days, high volatility days vs low volatility days and among different industry types. However, this study does not cover the examination of the evolution of herding conditional on such market characteristics. Second, the current study examines herd evolution at the aggregate market level. However, it could vary among different investor-types (for example, retail vs institutional investors) and different investment styles (for example, value vs. growth investing), and be related to factors other than investors' learning (for example, changes in trading rules and changes in investor composition). Accordingly, future studies could contribute the literature by examining the nature of herd evolution conditional on such micro and macro characteristics of a financial market.

Notes

1. The frontier equity indices provided by Morgan Stanley Capital International (MSCI), Russell, Standard & Poor and FTSE consistently classify the CSE as a frontier market.
2. See, for example, Arjoon and Bhatnagar (2017) and Yao, *et al.*, (2014).
3. See the literature reviews of Bikhchandani and Sharma (2000), Hirshleifer and Hong (2003) and Spyrou (2013).
4. The daily prices are used to test herd behavior since the findings of Christie and Huang (1995) and Tan, Chiang, Mason, and Nelling (2008) suggest that herding is more evident with the daily frequencies of data than weekly or monthly frequencies.
5. See, for example, Gavriilidis *et al.* (2016) and Guney *et al.* (2017).
6. See discussions of Bekiros, Jlassi, Lucey, Naoui, and Uddin (2017), T. C. Chiang *et al.*, (2010), Economou *et al.*, (2011), Focardi *et al.*, (2002) and Lux (1995) for weaknesses of the CSSD model and how they are overcome with the CSAD model.
7. See, for example, Barnes and Hughes (2002), Wilcox (2010) and Zhou and Anderson (2013) for statistical assumptions and weaknesses of the OLS regression.
8. Since the introduction of the QR by Koenker and Bassett (1978), it has been widely applied for econometrics and financial researches(Allen *et al.*, 2012). However, its application for the analysis of herding is very limited (Bekiros *et al.*, 2017).
9. See the discussion on the QR provided by Alexander (2008), Allen *et al.* (2012), Barnes and Hughes (2002), Cade and Noon (2003) and Xiao (2012).
10. The Eviews® Version 8 (2013) is used for obtaining the QR estimates.
11. The studies conducted by Chen and Wei (2005); Kocherginsky, He and Mu (2005); Koenker (1994); Koenker and Hallock (2000) provide a comparison of different methods available for determining confidence intervals under the QR procedure. They find that these methods slightly deviate from each other, however suggest the bootstrap technique as appropriate one for a study employing sample of less than 5,000 observations and less than 20 covariates.

12. Buchinsky (1995) and Machado and Silva (2013) find that the xy-pair bootstrap estimator enables for computing more valid standard errors than the other bootstrap estimators.
13. This procedure is consistent with Andrews and Buchinsky (2000) and Koenker and Hallock (2000).
14. The current study is not comparable to Xiaofang and Shantha (2017) in terms of the study sample since the former covers all the stocks whereas the latter considers only the stocks of the non-financial companies listed on the CSE. Thus, the contradictory evidence between the two studies may be due to the differences in the study samples.
15. See, for example, Arjoon and Bhatnagar (2017), Nguyen (2018) and Yao *et al.* (2014).

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