Prevalence of Herding and Market Sentiments

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Abstract

This study proposes a new herd measure for detecting prevalence of herding amongst a portfolio of stocks towards the market by exploiting the information contained in the cross-sectional stock price movements. We adopt the same underlying argument as Hwang and Salmon (2001, 2004, 2009), that is, the changes in the cross-sectional dispersion of the betas reflect investors’ sentiments towards the market. The betas are obtained from the multivariate linear regression model where the random errors are assumed to be normally distributed. By using the bootstrap method we determine the confidence interval of the herd measure. We applied the measure to a portfolio of stocks in the developing Malaysian market to study their herding behaviour in the years from 1993 to 2004 - a period spanning the market bull run in the early nineties, the 1997 Asian financial crisis and the subsequent recovery phase. The herding patterns found are closely linked to the prevailing market conditions and investor sentiments. Persistent herding was found in both rising and falling markets that were preceded by a sharp market reversal. Prolonged market falls – as seen in the financial crisis period and during the times when the market experienced technical corrections after a long period of ascent – practically run in tandem with persistent herding patterns. No significant herding was found when the market was confidently bullish in the pre-crisis period. In contrast, persistent herding was found during the short market rally that occurred when the market responded immediately to the stringent measures taken by the Malaysian government to arrest further deterioration in the financial system caused by the crisis. Overall, our study supports the intuition that herding is related to drastic changes in market conditions, especially so when the atmosphere of uncertainty is prevalent.

JEL Code: C12, C15, C31, G01, G12

Keywords: Herd measure, Cross-sectional stock price movements, Bootstrap method, Asian financial crisis, Market sentiments

1. INTRODUCTION

“First, in a world of uncertainty, the best way of exploiting the information of others is by copying what they are doing. Second, bankers and investors are often measured and rewarded by relative performance, so it literally does not pay for a risk-averse player to stray too far from the pack. Third, investors and bankers are more likely to be sacked for being wrong and alone than being wrong and in company.”

– An excerpt from Persaud’s acclaimed essay: Sending the Herd off the Cliff Edge

By incorporating psychology into finance and economics, proponents in this field (see Kahneman et al. 1982; Thaler, 1992; Shefrin, 1999) attempt to explain how the market participants’ perception and reaction to uncertainties could affect investment decisions, which in turn could influence security price movements. This theory categorically recognises the role of human behaviour as the driving force behind price movements and therefore, it emphasizes the need to include the human component in all financial studies in order to acquire a more comprehensive understanding.

In essence, behavioural finance contradicts the efficient market theory which advocates that, in a perfectly efficient market, investors are rational as they buy and sell devoid of emotions and hence,
the security prices should fully reflect all available information for all stocks at all times. It assumes that the investors are intuitively aware of a divergence between market price and its intrinsic value. When the market price falls below its perceived intrinsic value, the acquisitions of the stocks by the buyers would raise the price. And conversely, when the market price exceeds its intrinsic value, the action of sellers would then cause a fall in the price. Any mispricings would, therefore, be arbitrated away and a new equilibrium would then set in.

The growing popularity of behavioural finance is further spurred on by the uncovering of anomalies which cannot be explained by traditional finance theories. Behavioural finance does not believe in the existence of a rational man – in fact it attributes market aberrations like overreaction to news, herding among stocks, the January effect and other seasonal effects to investors' irrationality. It believes that markets are driven by fear and greed (Shefrin, 1999) and that trading is more often executed on emotional impulse – a fact observed by the US Federal Reserve chairman, Greenspan\(^2\), who coined the term ‘irrational exuberance’.

1.1 Investor Psychology, Herding Behaviour and Market Sentiments
Following the widespread financial crises in the last two decades, the issue of herding has become a topic of intense interest. It is intuitively recognised that in times of uncertainty and fear, many investors imitate the actions of other investors whom they assume to have more reliable information about the market. Prechter (2001) gives an interesting account of this behaviour from a biological point of view. He likens herding behaviour in financial circumstances to an innate primitive tool of survival. He explains that when individuals are faced with emotionally charged situations, unconscious impulses from the brain’s limbic system impel an inherent desire among them to “seek signals from others in matters of knowledge and behaviour and therefore to align feelings and convictions with those of the group”. When a sufficiently large number of investors flock together, they inadvertently create a prevailing consensus. This effect cumulates as the feeling of safety in numbers overrides individual judgements and perceptions. The impact can be sufficiently large enough to cause markets, sectors or stocks to collectively fall in or out of favour (Valance, 2001).

From the behavioural theorists' point of view, herding is a product of the two opposing emotional forces of fear and greed (Landberg, 2003). With regard to human emotions in trading, we would like to further extend this view by including two other types, namely remorse and pride. Fear, as associated with risk aversion, is a more powerful force that is linked to the feeling of remorse. Remorse is associated with the pain of losing money in making a bad financial decision, but is also the regret one feels when a lost opportunity to make money occurs. However, given a choice, human emotions would choose not to have lost, rather than not to have gained. The pain from a realised loss supersedes that of the regret of an unrealised gain. Greed, however, is linked to pride which is a pleasurable feeling of having made a right financial decision resulting in a gain. However, the pursuit of pleasure is not as strong a force as the flight from pain, whether real or perceived.

“Following the herd” is a human tendency that confirms the intrinsic overpowering of fear over greed. A decision to go with the herd is more emotionally comfortable because there is reduction in feelings of remorse if the move was wrong, but if the move was right, the loss of pride is a smaller price to pay. Herding however has fewer tendencies to result from greed and pride. The feelings of pleasure are intensified if a successful trade resulted from a brilliant unique idea rather than from following the crowd.

Herding is a gut reaction that is often done emotionally rather than after careful consideration of available information. Since fear is stronger than greed, herding should then theoretically occur more when fear is in abundance. In a fearful crisis situation, very often there is no time for reflection and herding is often a shortcut to a decision. A prolonged downturn is likely to breed fear, which in turn triggers irrational behaviour. \textit{En masse panic selling in such times of crisis may be the automatic reaction.}

In a prolonged market rally, greed should theoretically result in herding as emotional decisions are made to try to maximize profits. However, the associated emotion of pride puts a dampener on herding – the success is sweeter if one did not follow the crowd.

1.2 Definition of Herding
Herding, being a non-quantifiable behaviour, cannot be measured directly. It can only be inferred by studying related measurable parameters. Generally, it refers to a situation whereby a group of investors intentionally copy the behaviour of other investors by trading in the same direction over a period of time. Depending on the types of data being used in developing the models for herd measure, we can broadly identify two main categories of studies that have been conducted thus far. The first category of studies which focuses directly on the behaviour of investors requires detailed and explicit information on the trading activities of the investors and the changes in their investment portfolios. Examples of such herd measures are the LSV measure by Lakonishok et al. (1992) and the PCM measure by Wermers (1995).

The other category of studies views herding behaviour as a collective buying and selling actions of the individuals in an attempt to follow the performance of the market or any other economic factors or styles. Here, herding is detected by exploiting the information contained in the cross-sectional stock price movements. Christie and Huang (1995), Chang et al. (2000) and Hwang and Salmon (2001, 2004, 2009) are contributors of such measures.

1.3 Previous Studies
This study is motivated by the second category of studies on herding. We intend to propose yet another herd measure and then apply it to investigate the prevalence of herding of a portfolio of Malaysian stocks towards the market. Thus, we shall briefly review only those studies that formulate herd measures based on similar intuition.

One of the earliest studies that attempt to detect empirically herding behaviour in the financial markets comes from Christie and Huang (1995). They rationalise that during market stress – which is characterised by high volatility – herding of stocks towards the market is likely to be present. This is based on their argument that under such extreme market conditions, the investors are more likely to suppress their own beliefs and choose instead to follow the market consensus. The stock prices would then move in tandem with the market and as a result the cross-sectional dispersion of the individual stock returns would be expectedly low. This contradicts the Capital Asset Pricing Model (CAPM) which predicts that during market stress, large dispersions should be expected since individual stocks have different sensitivities to the market returns. Herding, however, is not implied by mere detection of low cross-sectional dispersion of returns. If the cross-sectional dispersion of the stock returns is low under the existence of large price changes, then the presence of herding is implied. By using the cross-sectional standard deviation of returns (CSSD) as a measure of the average proximity of individual stock returns to the market returns, Christie and Huang (1995) developed an empirical measure to test for herding behaviour in the U.S. equity market. Their results conclude that there was no significant evidence of herding in the period under study.

Chang et al. (2000) modified the approach suggested by Christie and Huang (1995). In place of CSSD, they use the cross-sectional absolute deviation of returns as a measure of dispersion. Their alternative empirical model also considers the rationale that CAPM not only predicts that the dispersions are an increasing function of the market return, but it is also linear. Thus, in the presence of herding behaviour the linear and increasing relation between dispersion and market return would no longer be true. Instead, the relation is increasing non-linearly or even decreasing. To accommodate the possibility that the degree of herding may be asymmetric in the up and the down markets, they run two separate regression models and the presence of herding in the up and the down markets is concluded by examining non-linearity in these relationships. They found no evidence of herding in the U.S. and Hong Kong markets and only partial herding in the Japanese market during the periods of extreme price movements. The results for the U.S. market are consistent with those obtained by Christie and Huang (1995). However, in the case of the Taiwanese and South Korean markets, they documented a dramatic decrease of return dispersions during both periods of extreme up and down price movements. This leads to their conclusion that there is significant evidence of herding in these emerging markets.

Among the latest to contribute to the development of herd measures are Hwang and Salmon (2001, 2004 and 2009). By examining the cross-sectional movements of the factor sensitivities instead of the returns, they formulated measures to capture market-wide herding as well as herding towards fundamental factors. The basis of their studies is founded on the discoveries from numerous empirical studies which show that the betas are in fact not constant as assumed by the conventional CAPM. They infer that this time-variation in betas actually reflects the changes in investor sentiment. In
Hwang and Salmon’s (2001) working paper, the herd measure is simply the cross-sectional dispersion of betas and evidence of herding is indicated by a reduction in this quantity. The confidence interval for this herd measure is computed based on their postulation that this herd measure follows an F-distribution.

In their later paper (2004), they circumvent the necessity to derive a correct distribution for the herd measure by adopting a different approach. They reckon that the action of investors intently following the market performance inadvertently upsets the equilibrium in the risk-return relationship and as a result, the betas become biased. They model the cross-sectional dispersion of the biased betas in a state space model, and using the technique of Kalman filter, they found that market-wide herding is independent of market conditions and the stage of development of the market.

Hwang and Salmon (2009) also investigated the effects of sentiment on herding. The herd measure premises on two aspects: the cross-sectional convergence within the market towards the market portfolio and the market-wide sentiment. Believing that herding is not necessarily short run in nature and could possibly be slow moving (as evidenced by incidences of financial bubbles), they study this behaviour over an extended time horizon using monthly rather than high frequency data. In this latest study, they adopt a non-parametric method to measure herding; hence overcoming the necessity to assume any particular parametric dynamic process for herding as the case in Hwang and Salmon’s earlier models. Their study on the U.S, U.K. and South Korean markets revealed evidence of more apparent herding when the direction the market is heading is obvious, regardless whether the market is bullish or bearish. In addition, they found that herding is neither driven by business cycles nor market movements.

The remainder of the paper is organised as follows. Section 2 discusses the objectives of this study. Section 3 expounds the theoretical considerations for the proposed herd measure and also discusses the bootstrap method used in determining its confidence interval. Section 4 shows how the herd measure is applied to a portfolio of stocks belonging to the developing Malaysian equity market. Section 5 tests the robustness of the herd measure. The final section discusses from the behavioural finance perspective, the implications of the empirical results obtained in Section 4 and draws a conclusion.

2. OBJECTIVES OF STUDY

There are two specific objectives to this study. Firstly, we propose a new herd measure to detect the degree of herding of a portfolio of stocks towards the market. In constructing this measure, we adopt the same definition of herding as Hwang and Salmon’s (2001, 2004, 2009) and also their underlying argument that the changes in the cross-sectional dispersion of the betas reflect investors’ sentiments towards the market. The measure is intended to detect the prevalence of herding and not the amount. As rightly pointed out by Hwang and Salmon (2004, 2009), herding, as related to market sentiment, is a latent and unobservable process. In fact, it is generally believed that herding among stocks or investors is ubiquitous; it is a matter of degree at any given point in time relative to another.

Secondly, we shall apply the herd measure to the realised returns of a portfolio of stocks listed in the Bursa Malaysia (formerly Kuala Lumpur Stock Exchange). To date, most of the studies on herding and its effects are conducted in the context of the markets in developed countries. There are no known studies which focus exclusively on the Malaysian equity market with regard to this phenomenon.

Being one of the countries severely affected by the 1997 Asian financial crisis, it would be interesting to investigate the degrees of herding in relation to this crisis. In each of these periods, a certain mood of investment prevailed. Through this study we hope to determine whether a change in investment sentiment was associated with any significant increase or decrease of market-wide herding. It would be interesting to investigate whether herding was associated with the unseen force driving the bull run of 1993. Rapid and en masse withdrawal of capital by foreign investors is often quoted as the main culprit that precipitated the 1997 Asian financial crisis. Was herding more rampant among the stocks during this crisis period? The differences in herd behaviour may also result from a change in investment atmosphere arising from government intervention. Another interesting issue to investigate
is whether the insulation effect from the imposition of capital controls at the beginning of the post-crisis period had in any way caused more herding among investors.

We use the multivariate linear model in the estimation of betas. The random errors are assumed to be normally distributed and the confidence interval of the herd measure is determined by the bootstrap method. In addition, we test the robustness of using an identified benchmark to conclude whether herding occurs in a particular month by varying the durations of the study period. To validate the plausibility of the herding results, we link the outcomes obtained to the prevailing market conditions and investors’ sentiments.

3. THEORETICAL CONSIDERATIONS

3.1 Underlying Principle and Formulation of the Herd Measure

3.1.1 Introduction

We formulate the herd measure based on the underlying principle that the cross-sectional dispersion of the market beta \( \beta_{im} \) (where \( i = 1, 2, \ldots, N \)) of all the \( N \) stocks in the portfolio indicates the degree of herding of these stocks towards the market. We obtain the market beta \( \beta_{im} \) from the multivariate linear model.

The market beta \( \beta_{im} \) is a measure of the change in stock return for a unit change in the market return. In more recent researches, it is no longer assumed to be constant but is time-varying instead. Under adverse market conditions when the stock prices are more volatile, the variation of the \( \beta_{im} \) of the individual stocks is likely to increase. However, since all stocks are equally affected, the cross-sectional dispersion of the \( \beta_{im} \) is not expected to alter. If the cross-sectional dispersion of the \( \beta_{im} \) does change significantly, it indicates that there is some ‘intentional movement’ of some individual stocks to follow the market.

3.1.2 Multivariate Linear Model

Consider a multivariate linear model:

\[
    r_{it} = \alpha_i + \beta_{im} r_{mt} + \sum_{k=1}^{K} \beta_{ik} f_{kt} + \varepsilon_{it}, \quad i = 1, 2, \ldots, N \text{ and } t = 1, 2, \ldots, n \tag{1}
\]

where \( r_i \) is the return of stock \( i \), \( \alpha_i \) is a constant, and \( \beta_{im} \) and \( \beta_{ik} \) are the coefficients on the market portfolio return (denoted by \( r_{mt} \)) and the \( k \)th factor (denoted by \( f_{kt} \)), respectively, at time \( t \). Both \( r_{mt} \) and \( f_{kt} \) are considered as observable values. Based on the classical assumptions, the random error \( \varepsilon_{it} \) is normally distributed with \( E(\varepsilon_{it}) = 0 \), \( \text{var}(\varepsilon_{it}) = \sigma_{it}^2 \), \( \text{cov}(\varepsilon_{it}, \varepsilon_{jt}) = \sigma_{ijt} \) for \( i \neq j \) and \( \text{cov}(\varepsilon_{it}, \varepsilon_{st}) = 0 \) for all \( i \) and \( j \), and \( t \neq s \). The \( K \) factors can be any observable quantities that are likely to have effects on stock price movements, for instance, macroeconomic factors, market capitalisations and financial ratios of the companies.

3.1.3 Cross-sectional Variance of Beta

Since we intend to study the herd behaviour at a monthly frequency, we shall assume that the time-varying alpha, betas and sigmas are constant within the short period of one month. Therefore for stock \( i \), we have

\[
    r_{it} = \alpha_i + \beta_{im} r_{mt} + \sum_{k=1}^{K} \beta_{ik} f_{kt} + \varepsilon_{it}, \quad i = 1, 2, \ldots, N \text{ and } t = 1, 2, \ldots, n \tag{2}
\]

where \( \alpha_i \), \( \beta_{im} \) and \( \beta_{ik} \) are the constant coefficients in a given month in which there are \( n \) trading days. Since the beta \( \beta_{im} \) of stock \( i \) is the primary concern of this study, we shall simply refer to it as the ‘beta’. The notation \( t \) in Eq. (2) is slightly different from that in Eq. (1). Here, it denotes the \( t^{th} \)
The cross-sectional expectation \( E_c \) of all the individual stocks in the market at time \( t \) constitutes the market portfolio return, that is,

\[
E_c \left[ r_{it} \right] = \frac{1}{N} \sum_{i=1}^{N} r_{it} = r_{mt}
\]

Thus, from Eq. (1), we obtain

\[
r_{mt} = E_c [\alpha_i] + r_{mt} E_c [\beta_{im}] + \sum_{k=1}^{K} f_{ki} E_c [\beta_{ik}] + E_c [\epsilon_{it}] \quad t = 1, 2, \ldots, n
\]

Taking the ordinary expectation \( (E) \) on both sides of Eq. (2), we obtain

\[
E_c [\alpha_i] + E_c (\beta_{im}) - 1 E [r_{mt}] + \sum_{k=1}^{K} E_c [\beta_{ik}] E [f_{ki}] = 0
\]

The variables in Eq. (3) are \( E_c [\alpha_i], E_c (\beta_{im}) \) and \( E_c [\beta_{ik}] \). In the case when the number of equations \( n \) is greater than the number of variables \( (K + 2) \), Eq. (3) would imply that

\[
E_c [\alpha_i] = 0, \quad E_c (\beta_{im}) = 1 \quad \text{and} \quad E_c [\beta_{ik}] = 0 \quad k = 1, 2, 3, \ldots, K
\]

Essentially, it means that in cross-sectional analysis, the average of the \( \beta_{im} \) is expected to be equal to 1 while the other coefficients average out to zero.

Ordinarily, at any given time \( t \), the stock price movements are supposedly independent of each other and we expect a wide range of \( \beta_{im} \) for the stocks, albeit an average of 1. However, in the presence of significant herding of the stocks towards the market, where more investors are imitating the general movement of the market, the range of \( \beta_{im} \) for the stocks is expected to be narrower. In effect, it means that a significant decrease in the cross-sectional variance of the betas would signify an increase in the degree of herding towards the market. The monthly herd measure based on the cross-sectional variance of the betas is given by

\[
H = \text{Var}_c (\beta_{im}) = E_c \left[ \beta_{im} - E_c (\beta_{im}) \right]^2 = E_c (\beta_{im} - 1)^2
\]

where

\[
H = \frac{1}{N} \sum_{i=1}^{N} (\beta_{im} - 1)^2
\]

3.1.4 Formulation of the Estimated Herd Measure

Below is the multivariate linear model for the return of stock \( i \) in a given month in matrix notation,

\[
r_i = X \beta_i + \epsilon_i
\]

where

\[
r_i = \begin{pmatrix} r_{i1} \\ r_{i2} \\ \vdots \\ r_{in} \end{pmatrix}, \quad X = \begin{pmatrix} 1 & f_{i1} & \cdots & f_{i1K} & r_{m1} \\ 1 & f_{i2} & \cdots & f_{i2K} & r_{m2} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & f_{in} & \cdots & f_{inK} & r_{mn} \end{pmatrix}, \quad \beta_i = \begin{pmatrix} \alpha_i \\ \beta_{i1} \\ \beta_{i2} \\ \vdots \\ \beta_{im} \end{pmatrix} \quad \text{and} \quad \epsilon_i = \begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \vdots \\ \epsilon_{in} \end{pmatrix}
\]

We apply the following orthogonal transformation (specifically known as Householder transformation) to Eq. (6) in order to simplify computation:

\[
H^+ r_i = H^+ X \beta_i + H^+ \epsilon_i
\]

which can be re-expressed as
\[ r_i^* = D^U \beta_i^* + \epsilon_i^* . \]  

(7)

\[ D^U \] is an upper triangular matrix with a zero matrix beneath it, that is

\[
D^U = \begin{pmatrix}
  d_{11} & d_{12} & d_{13} & \cdots & d_{1K+1} & d_{1K+2} \\
  0 & d_{22} & d_{23} & \cdots & d_{2K+1} & d_{2K+2} \\
  0 & 0 & d_{33} & \cdots & d_{3K+1} & d_{3K+2} \\
  \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
  0 & 0 & \cdots & \cdots & d_{K+2,K+2} \\
  0 & 0 & \cdots & \cdots & 0 & 0 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
  0 & 0 & \cdots & \cdots & 0 & 0 \\
\end{pmatrix}
\]

The following \((K+2)\) equations are then derived:

\[
\begin{align*}
  r_{i1}^* &= d_{11} \alpha_i + d_{12} \beta_{i1} + \ldots + d_{1K+2} \beta_{iK+2} + \epsilon_{i1}^* \\
  r_{i2}^* &= d_{22} \beta_{i1} + d_{23} \beta_{i2} + \ldots + d_{2K+2} \beta_{iK+2} + \epsilon_{i2}^* \\
  \vdots &= \vdots \\
  r_{i,K+2}^* &= d_{K+2,K+2} \beta_{iK+2} + \epsilon_{i,K+2}^* \\
\end{align*}
\]

(8)

Letting \( d_{K+2,K+2} \beta_{iK+2} = \phi_{i,K+2} \), the last equation in Eq. (8) can be rewritten as

\[
  r_{i,K+2}^* = \phi_{i,K+2} + \epsilon_{i,K+2}^* \\
\]

The ordinary least squares estimate of the \( \beta_{im} \) is

\[
  \hat{b}_{im} = \hat{\beta}_{im} = r_{i,K+2}^* / d_{K+2,K+2} = (\phi_{i,K+2} + \epsilon_{i,K+2}^*) / d_{K+2,K+2} \\
\]

(9)

The first two moments of \( \hat{b}_{im} \) are:

\[
\begin{align*}
  E(\hat{b}_{im}) &= E\left(r_{i,K+2}^*/d_{K+2,K+2}\right) = E\left[(d_{K+2,K+2}\beta_{im} + \epsilon_{i,K+2}^*)/d_{K+2,K+2}\right] \\
  E(\hat{b}_{im}^2) &= E\left[(d_{K+2,K+2}\beta_{im} + \epsilon_{i,K+2}^2 + 2d_{K+2,K+2}\beta_{im}\epsilon_{i,K+2}^*)/d_{K+2,K+2}\right] \\
\end{align*}
\]

(10)

(11)

Following the assumption of normality in distribution of random errors, i.e. \( \epsilon_{it} \sim N\left(0, \sigma_i^2\right) \), \( \epsilon_{it}^* \) follows the same distribution since \( \epsilon_{it}^* \) is obtained by an orthogonal transformation of the \( \epsilon_{it} \) [see Eq. (7)].

Thus, from Eq. (10) and Eq. (11),

\[
\begin{align*}
  E(\hat{b}_{im}) &= \beta_{im} \\
  E(\hat{b}_{im}^2) &= \beta_{im}^2 + \sigma_i^2 \Psi \\
\end{align*}
\]

(12)

(13)

where \( \Psi = 1/(d_{K+2,K+2}^2) \).

The variance of \( \hat{b}_{im} \) would then be given by

\[
\text{var}(\hat{b}_{im}) = E(\hat{b}_{im}^2) - E^2(\hat{b}_{im}) = \sigma_i^2 \Psi \\
\]

and hence the distribution of \( \hat{b}_{im} \) is
\[ b_{im} \sim N\left(\beta_{im}, \sigma_i^2\psi\right) \]

In a given month, the herding effect corresponds to the deviation of \( \beta_{im} \) from 1 [note that \( E_c(\beta_{im}) = 1 \)]. This deviation may be positive or negative, depending on the value of \( \beta_{im} \). Taking \( h_i \) as the theoretical but unknown degree of herding towards the market return for stock \( i \), we obtain

\[ h_i = \left[ \beta_{im} - E_c(\beta_{im}) \right]^2 = (\beta_{im} - 1)^2 \]

The estimated herd measure \( (b_{im} - 1)^2 \), is biased. Hence, we consider an alternative estimated herd measure of stock \( i \) in a given month which is given by

\[ \hat{h}_i = (b_{im} - 1)^2 - S_i^2\psi \quad (14) \]

where \( S_i^2 = \left( \sum_{t=K+1}^{n} e_{it}^2 / [n - (K + 2)] \right) \) is an unbiased estimate of \( \sigma_i^2 \).

Thus, in a given month, the theoretical and estimated relative degrees of herding for \( N \) stocks in a given portfolio are, respectively,

\[ H = \frac{1}{N} \sum_{i=1}^{N} (\beta_{im} - 1)^2 \quad (15) \]

and

\[ \hat{H} = \frac{1}{N} \sum_{i=1}^{N} \left[ (b_{im} - 1)^2 - S_i^2\psi \right] \quad (16) \]

### 3.2 Confidence Interval of the Herd Measure – the Bootstrap Method

Having determined the estimate \( \hat{H} \), it is essential to compute a satisfactory confidence interval for \( H \). This confidence interval is based on some property that renders it a certain specified high probability of containing the true population value.

The distribution of \( \hat{H} \) is unknown. But by visual inspection, the distributions\(^3\) of several sets of 100000 values of \( \hat{H} \) appear to be unimodal and only slightly skewed. Hence, this suggests the plausibility of using bootstrap procedure to obtain the confidence interval of \( H \).

The advantage of the bootstrap method is that it does not require \textit{a priori} assumptions about the distribution of the estimate. This procedure takes the sample estimates as the true values. The original bootstrap procedure involves non-parametric re-sampling where the bootstrap sample is formed by drawing with replacement from the sample. However, under the assumption that the returns of the stocks are normally distributed, the bootstrap re-sampling is carried out parametrically instead.

We recapitulate that the unbiased estimated herd measure of stock \( i \) and the unbiased estimated herd measure of all \( N \) stocks in the portfolio are given by Eq. (14) and Eq. (15), respectively. Hence, the unbiased estimate of \( \hat{H} \) based on the bootstrap sample is given by

\[ \tilde{H} = \frac{1}{N} \sum_{i=1}^{N} \left[ (\tilde{b}_{im} - 1)^2 - 2S_i^2\psi \right] \quad (17) \]

where \( \tilde{b}_{im} \) and \( S_i^2 \) represent, respectively, the estimated values of the coefficient and the variance of the random errors based on the bootstrap sample.
The bootstrap samples are generated based on \( \{X, (\hat{\beta}_i, 1 \leq i \leq N), \hat{A}\} \) where \( \hat{\beta}_i \) is a column vector of the least square estimates of \( \alpha, \beta_{ik}, \beta_{im} \), denoted by \( a_i, b_{ik}, b_{im} \), and \( \hat{A} \) is the estimated variance-covariance matrix of the random errors. The steps involved in the determination of \( \hat{A} \) and the generation of bootstrap samples are outlined in APPENDIX A.

We generate \( M^* \) bootstrap samples. The bootstrap confidence interval of \( H \) is then determined by the ranking method. This classical ranking method involves arranging the \( M^* \) values of \( \hat{H} \) in an ascending order: \( \tilde{H}^{(1)}, \tilde{H}^{(2)}, ..., \tilde{H}^{(M^*)} \). The lower and upper boundaries of the \( 100(1-\alpha) \% \) confidence interval of \( H \) are given by

\[
L = \hat{H}^{(k)}, \quad U = \hat{H}^{(M^*+1-k)}
\]

where \( k = M^* \left( \alpha/2 \right) \) and \( k \) is an integer. If \( k \) is not an integer, we then adopt the convention of Efron and Tibshirani (1993) by setting \( k = \left( \left\lfloor M^* + 1 \right\rfloor \left( \alpha/2 \right) \right) \), that is, the largest integer that is less than or equal to \( \left( M^* + 1 \right) \left( \alpha/2 \right) \). As a rule of thumb, it is recommended to use \( M^* \geq 1000 \) in order to obtain stable bootstrap confidence intervals (see Efron and Tibshirani, 1993; Chernick, 1999).

As emphasised earlier, the measure is not meant to measure quantities of herding; instead it aims to measure the relative degrees of herding of a portfolio of stocks towards the market. The arithmetic mean of all the monthly values of \( \hat{H} \) for the duration of period under study is used as the benchmark for this purpose. Setting \( \alpha = 0.05 \), we are 95% confident that the actual unknown value of \( H \) lies within \( L \) and \( U \). If the value of \( U \) is less than or equal to this benchmark, then we conclude with a 95% level of confidence that there is herding. On the other hand, we cannot make a conclusion of herding at the 95% confidence level for the following two cases: (1) The benchmark is less than \( U \) but more than \( L \), and (2) The benchmark is less than or equal to \( L \).

4. APPLICATION OF THE HERD MEASURE

4.1 Data

In this study we apply the herd measure to a portfolio of 69 constituent stocks of the Kuala Lumpur Composite Index (KLCI) to study the profile of herding towards the market from January 1993 to December 2004 – a period straddling the market bull run in the early nineties, the 1997 Asian financial crisis and subsequently the supposedly recovery phase. The criterion for choosing these 69 stocks is based on the fact that these stocks have been continuously listed in the KLCI since 1993. As at December 2005, these 69 stocks constitute about 50% of the total market capitalisation. The KLCI is used as a proxy for the market portfolio. The multivariate linear model is also kept simple by using the basic Market Model where no factors are included (that is, \( K = 0 \)).

The daily stock returns and market returns are computed as follows:

\[
r_{it} = \ln \left( \frac{p_{it}}{p_{i,t-1}} \right) \quad \text{and} \quad r_{mt} = \ln \left( \frac{p_{mt}}{p_{m,t-1}} \right),
\]

where \( p_{it} \) and \( p_{mt} \) represent the daily closing price on day \( t \) for stock \( i \) and the market, respectively.

From the basic Market Model, we estimate the values of \( a_i, b_{im} \) and \( \hat{\sigma}_i^2 \) for each month.

The profile of market volatility is also taken into consideration. The market volatility in a given month is measured by the standard deviation of the daily closing prices of the market, that is,
\[ \hat{\sigma}_m = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (r_{mt} - \bar{r}_m)^2} \bigg/ (n-1) \]

where \( n \) is the number of trading days in the month and \( \bar{r}_m = \frac{1}{n} \sum_{t=1}^{n} r_{mt}. \)

### 4.2 Methodology and Empirical Results

The occurrence of herding was analysed in relation to the three periods (given below) as determined by Goh et al. (2005).

- Pre-crisis period – January 1993 to July 1997
- Crisis period – August 1997 to August 1998
- Post-crisis period – September 1998 to December 2004

Figure 1 shows the distribution of the 144 monthly values of \( \hat{H} \) obtained. The distribution of \( \hat{H} \) is not normal; instead it is slightly positively skewed and leptokurtic. The benchmark for the determination of existence of herding is 0.571, the arithmetic mean of \( \hat{H} \). Herding is said to be present in a given month if the value of \( U \) is lower than or equal to this benchmark.

![Figure 1](image)

**Figure 1** Histogram of \( \hat{H} \)

The results from the bootstrap method of obtaining confidence interval of \( H \) are shown in Table 1. The presence of herding is indicated by the letter \( h \). The numerical values can be provided by the authors upon request.
Table 1  Herding Results

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**Panel B: Crisis Period**

| Year |  |  |  |  |  |  |  |  |  |  |
|------|---|---|---|---|---|---|---|---|---|
| 1997 | h   | h   | -   | -   | h   | h   | h   |
| 1998 | h   | h   | -   | -   | -   | h   | h   |

**Panel C: Post-crisis Period**

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**Note:** The letter h indicates ‘Herding occurs’.

In order to study herding in relation to the prevailing market trends and market volatility, a graphical approach would be more informative. The values of $L$, $\hat{H}$ and $U$ for each month are plotted in a vertical line which is named as range plot of the herd measure. The graphs of range plots are charted chronologically with the graph showing the end-of-the-month closing values of the KLCI and the graph for the monthly estimated market volatilities. The composite graphs are shown in Figure 2. The red horizontal line shown in the graph of range plots is the benchmark line. The red vertical lines that traverse all three graphs in each chart mark the months where discernible occurrence of herding is identified.
5. TESTING ROBUSTNESS OF THE HERD MEASURE

The evidence of herding is dependent on the arithmetic mean of \( \hat{H} \) or the benchmark for the period under study. We conclude that there is herding in a given month if \( U \) is less than or equal to this benchmark. Varying the period of study will certainly change this benchmark.

To verify that this proposed procedure in drawing conclusion on herding outcome is robust, we proceed to vary the periods of study. We differentiate the 12-year study period into three different periods of study – the pre-crisis period, the crisis period and the post-crisis period. When the period of study is stipulated as the ‘pre-crisis period’, the benchmark is given by the arithmetic mean of \( \hat{H} \) for all the months in this period only. Likewise, the benchmarks are calculated for the two other periods of study. To avoid possible confusion, we shall label these periods of study as \( D_1 \), \( D_2 \) and \( D_3 \), and their respective benchmarks are 0.50834, 0.33678 and 0.65658. The herding outcomes through the two methods for the study periods \( D_1 \), \( D_2 \) and \( D_3 \), are compared to the corresponding herding outcomes reported in Panel A, Panel B and Panel C in Table 1. The results are shown in Tables 2, 3 and 4.

An analysis of Table 2 to Table 4 reveals that, with the exception of a few months where the occurrences of herding do not coincide, the patterns of persistent herding are generally overlapping. This shows that we can still obtain similar results despite changing the periods of study.
Table 2: A Comparison of Herding Results for Pre-crisis Period

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Note: The letter h indicates ‘Herding occurs’. The notation T1A represents the set of herding outcomes from the Panel A of Table 1.

Table 3: A Comparison of Herding Results for Crisis Period

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Note: The letter h indicates ‘Herding occurs’. The notation T1B represents the set of herding outcomes from the Panel B of Table 1.

Table 4: A Comparison of Herding Results for Post-crisis Period

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6. IMPLICATIONS OF EMPIRICAL RESULTS AND CONCLUDING REMARKS

In this section, we shall attempt to explain the pattern of herding behaviour that we obtained by linking it chronologically to the market movements, the prevailing market sentiments and the events that had taken place. In their study on herd behaviour in the financial markets, Bikhchandani and Sharma (2001) have pointedly highlighted that “the investment decisions of early investors are likely to be reflected in the subsequent price of the assets”. Without the actions of the investors, obviously there would be no price movements. Therefore, it is certainly justifiable to ‘read’ the intentions and psychology of the investors from the characteristics derived from studies that use realised data.

6.1 Pre-crisis period (January 1993 to July 1997)

During the market rally all through 1993, herding was not detected at all. Instead, it was noted only after the sharp market decline in early 1994.

Investor’s success was almost certain regardless of choice of stocks during this period of market bull-run. Fear was minimal and in its place was exuberance and over-confidence. There was no necessity to seek safety in numbers since there was no perceived threat. This is reflected in our study where no herding was found in that period of unrelenting market rise. In early 1994, the inevitable market correction brought a calamitous downtrend. It was then evident that the investment climate had changed, and in fear and uncertainty, investors looked to one another for direction. Periods of persistent herding appeared all through 1994 and 1995, typically at market peaks and troughs.

For the remaining months in the pre-crisis period, the market was going through the usual phases of rising and falling prices but generally trending upwards. Herding was still detected, although intermittently.

6.2 Crisis Period (August 1997 to August 1998)

The Malaysian market tumbled from a peak of 1200 points to less than half its value by August 1998. Strong evidence of herding was shown in the period from July 1997 to February 1998.

The patterns of herding in the two-year period of 1997 to 1998 speak volumes of the effect of the 1998 Asian financial crisis. The clearly persistent herding shown from July 1997 to February 1998 corresponded to the time of crisis period when the Malaysian ringgit was floated in reaction to the ensuing pandemonium of currency devaluation that spread rapidly throughout the Southeast Asian region. The high market volatility in this period shows that there were rapid changes in prices.
However, rather unexpectedly, significant herding disappeared altogether in the next three months even though the market was falling steeply.

In the face of so much uncertainty, the investors were probably adopting a cautious attitude. This postulation is supported by the marked decrease in market volatility during this period.

Persistent herding started to reappear in the few months before the market reached its lowest point (in August 1998) in the entire twelve-year period of our study.

6.3 Post-crisis period (September 1998 to December 2004)

Our results show a pattern of persistent herding in the next three months, but this time in an ascending market. This is an interesting observation as it is in contrast to the period of market rally in 1993 where no herding behaviour was picked up by the measure.

In order to curb the excessive volatility in the foreign exchange rate, on 1 September 1998, the Malaysian government imposed capital controls that pegged the Malaysian ringgit to the US dollar. The market responded immediately and positively. The market was highly volatile in that month as confirmed by the sharp spike shown in the graph of market volatility. This evidence of herding following the imposition of capital controls may well reflect the investors' apprehensive sentiments at that point in time. Such drastic measures adopted by the government were hitherto without precedence and the implementation was fraught with uncertainty and fear. The investors probably believed that the market had hit rock-bottom and they would not want to miss out on the opportunity to reap some profits or to regain their losses. However, under such circumstances, it is not surprising that persistent herding occurred. In contrast, the market sentiments during the continuous rise of 1993 were that of confidence. Perhaps this observation offers circumstantial evidence that herding behaviour is associated with uncertainty and fear.

In 2000, persistent herding occurred again after some unprecedented developments.

In February 2000, Bank Negara Malaysia enforced the merger of 50 banks into 10 banking groups by year end. This also led to consolidation of the local stock broking industry with mergers and acquisitions among local stock broking companies (source: Securities Commission 2000 Annual Report). In an already declining market, such unusual developments involving financing and transacting of equities were certain to have an unsettling effect on investors and would heighten negative sentiments.

From the year 2001 onwards, the market generally drifted sideways, with no marked price swings. Except for the few sporadic cases, the results do not show much persistent herding behaviour in that period.

6.4 Concluding remarks

We found patterns of herding which can be explained by the prevailing market conditions and investor sentiments in the developing Malaysian stock market. Herding was found to be more prominent in both rising and falling markets that were preceded by a sharp market reversal. No clear herding was found when the market was confidently bullish in the early nineties. Prolonged market falls – as seen in the financial crisis period and during the times when the market experienced technical corrections after a long period of ascent – practically run in tandem with persistent herding patterns. In period of crisis, herding is expected since in the face of uncertainty and fear, investors would likely seek safety in numbers. Not surprisingly, the crisis period recorded the highest proportion of herding incidences. Herding was very pronounced during the short market rally that occurred when the market responded immediately to the stringent measures taken by the Malaysian government to arrest further deterioration in the financial system caused by the crisis. However, the resulting market rally was unlike that in the early nineties when the market sentiments were radically different. This evidence of herding at the beginning of the post-crisis period may well reflect the prevailing mood of apprehension in reaction to the measures taken by the government. Overall, our study, using the proposed new measure, supports the intuition that herding is related to drastic changes in market conditions, more so when the atmosphere of uncertainty is prevalent.
REFERENCES


1 This essay won the first prize on Global Finance for the year 2000, in the Institute of International Finance, a competition in honour of Jacques de Larosiere.

2 Alan Greenspan is an American economist who served as Chairman of the Federal Reserve of the United States from 1987 to 2006.

3 We simulated four-stock and ten-stock models to investigate performance of the confidence intervals of $H$ obtained by the parametric bootstrap method.

APPENDIX A

On the same trading day, we expect some degree of contemporaneous correlation among the stock returns. Hence, the contemporaneous correlation among the errors of the stocks must also be taken...
into consideration. Taking $\varepsilon_{id_1}$ as the error of stock $i$ on day $d_1$ and $\varepsilon_{jd_2}$ as the error of stock $j$ ($i \neq j$) on day $d_2$, where $d_1$ and $d_2$ are two different days, we assume that
(a) $\varepsilon_{id_1}$ is correlated to $\varepsilon_{jd_1}$
(b) $\varepsilon_{id_1}$ is not correlated to $\varepsilon_{jd_2}$
(c) $\varepsilon_{id_1}$ is not correlated to $\varepsilon_{jd_2}$

To circumvent the problem of contemporaneous correlation, we transform the vector $\mathbf{E}_t$ of correlated errors to a vector of non-correlated errors as shown below:

$$S_t = V^T E_t$$  \hspace{1cm} (A.1)

or

$$\begin{pmatrix}
  s_{t1} \\
  s_{t2} \\
  \vdots \\
  s_{tN}
\end{pmatrix} =
\begin{pmatrix}
  v_{11} & v_{21} & \cdots & v_{N1} \\
  v_{12} & v_{22} & \cdots & v_{N2} \\
  \vdots & \vdots & \ddots & \vdots \\
  v_{1N} & v_{2N} & \cdots & v_{NN}
\end{pmatrix}
\begin{pmatrix}
  \varepsilon_{t1} \\
  \varepsilon_{t2} \\
  \vdots \\
  \varepsilon_{tN}
\end{pmatrix}$$

In effect, the columns of $V$ are the eigenvectors of the variance-covariance matrix $A$ of the random errors, that is

$$AV = VD$$  \hspace{1cm} (A.2)

where $D$ is the diagonal matrix of eigenvalues. Converse to Eq. (A.1), we have

$$E_t = VS_t$$  \hspace{1cm} (A.3)

The bootstrap samples are generated by following the steps below.

1. Find the residuals $e_{it} = r_{it} - \left(a_i + b_{i1}f_{it} + b_{i2}f_{2t} + \ldots + b_{ik}f_{kt} + b_{im}r_{mt}\right)$.  \hspace{1cm} (A.4)

2. Find the estimated variance-covariance matrix, $\hat{A}$, through the formulae below:
   (a) Estimated variance for stock $i$:
   $$S_i^2 = \hat{\sigma}_i^2 = \frac{1}{n - (K + 2)} \sum_{t=1}^{n} e_{it}^2$$  \hspace{1cm} (A.5)
   (b) Estimated covariance for stock $i$ and $j$:
   $$\hat{\sigma}_{ij}^2 = \frac{1}{n} \sum_{t=1}^{n} e_{it}e_{jt} \text{ where } i \neq j.$$  \hspace{1cm} (A.6)

3. Find matrix $\hat{V}$ formed by the eigenvectors of $\hat{A}$ and obtain the following relationship between the bootstrap version of the vector of correlated errors $\hat{E}_t$ and uncorrelated errors $\hat{S}_t$:

$$\hat{S}_t = \hat{V}^T \hat{E}_t$$  \hspace{1cm} (A.7)
$$\hat{E}_t = \hat{V} \hat{S}_t$$  \hspace{1cm} (A.8)

4. From Eq. (A.7), we obtain

$$\hat{\sigma}_{ij}^2 = \text{Var}\left(\hat{S}_{ti}\right) = \left(\sum_{p=1}^{N} \hat{\sigma}_i^2\right) \hat{\sigma}_j^2 + 2 \left(\sum_{p=1}^{N-1} \sum_{q=p+1}^{N} \hat{\sigma}_{pi} \hat{\sigma}_{qi}\right) \hat{\sigma}_{ij} \text{ for } i, j = 1, 2, \ldots, N \text{ and } i \neq j.$$
5. Generate \( \tilde{s} = [\tilde{s}_{11} \, \tilde{s}_{12} \, \ldots \, \tilde{s}_{Ni}]^T \) using \( \tilde{s}_i \sim N(0, \sigma_i^2) \).

6. Find \( \tilde{\epsilon}_i = \hat{v}_{i1} \tilde{s}_{1i} + \hat{v}_{i2} \tilde{s}_{2i} + \ldots + \hat{v}_{iNi} \tilde{s}_{Ni} \) using Eq. (A.8).

7. Find the bootstrap sample using \( \tilde{r}_i = a_i + b_{i1} f_{1i} + b_{i2} f_{2i} + \ldots + b_{ik} f_{ki} + b_{im} r_{mi} + \tilde{\epsilon}_i \).

8. Find \( \tilde{\epsilon}_i^* = H^* \tilde{\epsilon}_i \), where vector \( \tilde{\epsilon}_i \) is formed by \( \tilde{\epsilon}_i \), and \( H^* \) is the Householder matrix.

9. Find \( \tilde{r}_{i,K+2} = d_{K+2,K+2} \tilde{b}_{im} + \tilde{\epsilon}_{i,K+2}^* \).

10. Find \( \tilde{b}_{im} = \frac{\tilde{r}_{i,K+2}^*}{d_{K+2,K+2}} \) and \( \tilde{S}_i^2 = \frac{1}{n-(K+2)} \sum_{t=K+3}^{n} \tilde{\epsilon}_{it}^2 \).

11. Find \( \tilde{H} = \frac{1}{N} \sum_{i=1}^{N} \left[ (\tilde{b}_{im} - 1)^2 - 2\tilde{S}_i^2 \psi \right] \).