1. INTRODUCTION

Methodologically, empirical investigations that seek to test for evidence of herding behaviour among investors are predominantly based on the conventional techniques: cross–sectional standard deviation, hereafter CSSD, and cross–sectional absolute deviation, hereafter CSAD. The former approach, a measure of average proximity of individual asset returns to the realised market average was proposed by Christie and Huang in 1995 and later updated in 2000 by Chang, Cheng and Khorana. These methods of analyses mainly employ the dummy regression and the ordinary least squares regression, hereafter OLS, models to study the linear and nonlinear relationship between return dispersion and average market portfolio return, henceforth market return, as a means of detecting investors' herding behaviour. Herding behaviour has become an important subject in the economic literature especially in the context of the recent financial crunches.

According to Christie and Huang (1995), investors primarily hinge on the overall market condition in taking decisions relating to their investments plans. They further state that rational asset pricing models dictate that return dispersion continually increases with market return. Additionally, they observe that investors rely on their private beliefs which are mostly different in taking investment decision especially during the normal market period. However, during periods of market stress (bearish/bullish phase), investors subdue their private beliefs and conform to the prevailing market consensus and by so doing deviate from their investment strategies.

Thus, individual asset returns cluster around the market return leading to herding becoming more prevalent. They posit that there exists an inverse linear relationship between return dispersion and market returns during such periods. On the other hand, Chang, Cheng and Khorana (2000) suggest that the relationship as proposed by Christie and Huang (1995) may also be nonlinear because of asymmetry especially during periods of market stress. According to Chen, Demirer and Kutan (2010), herding behaviour is more likely to occur in financial markets especially during periods of extreme market movements where investors' appetite to follow the herd increases.

In the conventional framework, both methods measure market return dispersion/spread and use the arithmetic mean as a measure of market return. Even though the arithmetic mean is a known measure of central tendency and is sensitive to outliers, the traditional measures fail to address this problem. However, Chang, Cheng and Khorana (2000) proposed a method which sort to address and counter the weaknesses in the former approach only solve the problem by taking the absolute deviation of the mean vis–à–vis the square mean deviation as in the case of the former method in deriving the return dispersion/spread.

On another front, Hwang and Salmon (2001) proposed a new method for testing evidence of herding behaviour. The motivation of their approach was derived from the Capital Asset Pricing Model (CAPM). According to Hwang and Salmon, a change of asset betas from their equilibrium position measures the level of herding behaviour in financial markets. They posited that the pioneering methods of detecting herding behaviour centred mainly on the cross–sectional variation of returns. Hence their proposed technique; however, focused on the risk–return relationship. Contrary to the pioneering models, Hwang and Salmon used assets betas as a proxy to measure herding behaviour. They observe that when investors follow the collective market consensus, asset betas dispersion turns to be smaller.

Despite the identified model disadvantages of the traditional methods of detecting herding behaviour among investors, the alternative approach suggested by Hwang and Salmon (2001) was also not without weaknesses. One key drawback of using the methodology was that it was difficult to obtain expected results due to insignificant coefficients.

In recent decent years, alternative models have been suggested for capturing the market phenomenon. Even though the newly proposed models have been shown to be robust and tractable compared to the conventional approaches, they have shown inconsistent results.

Herding among investors has been documented in behavioural finance literature as irrational. Behavioural economics has focused on the study of the rationality of investors as well as on the cognitive processes involved in the financial decisions made by investors, specifically, in their capital market investment decisions (Fromlet, 2001). Traditional economic theories are primarily built on the hypotheses of rational investors and efficient markets. These theories have been contested by critics working in the field of behavioural economics. The field of behavioural economics arose out of criticism of traditional economics.

Herding behaviour is a common characteristic of financial and stock markets. According to Kremer and Nautz (2011), the tendency to accumulate on the same side of the market shows evidence of herding behaviour. They further opined that the market phenomenon might disrupt stability and efficiency of financial markets. Likewise, the presence of herding makes diversification difficult for investors. Chang, Cheng and Khorana (2000) posited that to maintain the same level of diversification, a larger number of securities are required, when investing in a herding driven market than in a normal market. According to Hwang and Salmon (2001), herding can lead to mispricing of stocks as a result of bias evaluation and analysis of expected stock performance. In the last two decades, herding behaviour has been studied extensively as a result of its adverse consequences in financial markets.

Several empirical studies have analysed the existence of herding behaviour among pension and mutual fund managers (see Lobao and Serra (2007); Gallagher and Jarnecic (2004); Clement and Tse (2005); Wylie (2005); Andreu *et al*. (2009); Huang *et al*. (2010); Sarpong and Sibanda (2014)) in specific financial markets.

Likewise, other studies (see Welch (2000); Ashiya and Doi (2001); Lamont (2002); Gleason and Lee (2003); Clement and Tse (2005); Lin *et al*. (2011)) investigated for evidence of herding behaviour among financial analysts. However, the findings of these studies in both advanced and emerging markets were inconclusive. A set of related papers (Chang *et al*. (2000); Lao and Singh (2011); Economou *et al*. (2011)) have established that emerging markets are more prone to the behavioural bias of herding as a result of its market characteristics than the advanced market.

Recent evidence shows that a different number of techniques have been used to test herding behaviour in both advanced and emerging financial markets (see, for example, Saastamoinen (2008); Chiang *et al*. (2010); Fu (2010); Bonfim and Kim (2014)). For many, if not most studies in the recent period have predominantly focused on advanced capital markets with limited studies on emerging market specifically in Africa where the market phenomenon is known to be prevalent. Recently published research has come to sharply divergent conclusions largely as a consequence of the models used (Demirer and Kutan (2006); Chan *et al*. (2007); Zhou (2007); Tan *et al.* (2008); Chiang *et al*. (2010); Mahmud and Tiniç (2015)). Therefore, the approach taken matters.

For example, employing CSSD and CSAD method, the following studies show different findings. First, Demirer and Kutan (2006) found no evidence of herding behaviour in the Chinese market. Second, Chan *et al*., (2007), found significant empirical evidence of herding in both Shanghai and Shenzhen B–type market during periods of extreme market conditions. However, they report a weaker evidence to support herding behaviour in A–type market. Likewise, Zhou (2007) found proof of herding in both A– and B–type markets. Tan *et al*., (2008), also found evidence of herding behaviour in A–type shares market.

On the other front, Chiang *et al*. (2010) used both the quantile regression model and rolling regression method to test evidence of herding behaviour in the Chinese stock market. They used the quantile regression model to examine the A–and B–type stock markets while they employed the rolling regression method to study the Chinese capital market. Their results failed to reject the existence hypothesis of herding behaviour in both markets.

On the other hand, Mahmud and Tiniç (2015) report of new evidence of herding behaviour in the Chinese financial markets (A– and B–type) by employing non–parametric kernel regression model. Their results show statistically significant evidence of herding behaviour in the A–type market under extremely high and low market returns. According to the authors, in the B–type market, the results showed only weak evidence of herding behaviour.

While literature in this field is growing, there is limited empirical research work that seeks to analyse and report herding trends in South Africa's financial market. In South Africa, empirical studies of herding behaviour in the Johannesburg Stock Exchange, hereafter JSE, have predominantly been centred on either the market as a whole or a specific industry using mainly the conventional methods (Gilmour and Smit (2002); Seetharam and Britten (2013); Sarpong and Sibanda (2014); Niyitegeka and Tewari (2015)).

Gilmour and Smit (2002) report of evidence of "institutional" herding behaviour in the unit trust industry of the JSE at a certain level of volatility. The authors concluded that the greater the volatility, the greater the degree of herding of unit trusts.

Using the All Share Index (ALSI) as well as all shares listed on the JSE from 1995 to 2011, Seetharam and Britten (2013) examined investors for evidence of herding behaviour. The authors used the two conventional methods and an alternative technique proposed by Hwang and Salmon (2001) to analyse their data. They found evidence of herding behaviour but only during the bear market phase.

Sarpong and Sibanda (2014) investigated evidence of herding behaviour among 41 institutional investors and the performance of mutual funds in South Africa. Herding measure of trading (Lakonishok *et al.* (1992)) was employed to analyse herding behaviour from 2006 to 2012. The authors reported of herding behaviour among the fund managers and concluded that the behaviour also affected the performance of their funds.

On the other hand, Niyitegeka and Tewari (2015) used an alternative technique, the autoregressive distributed lag approach (ARDL) to cointegration to examine the short–and long–term dynamics of top hundred (100) stocks on the JSE by market capitalisation. The study used data for the period August 2006 to August 2011. They found evidence of herding behaviour in the JSE during bull market periods. No proof of herding behaviour was found during bear market periods.

Selected studies have reported findings of herding behaviour in specific industries as well as the entire financial market as a whole in the JSE. These studies, however, fail to extend to validating the existence or absence of the market characteristic in specific sectors of the selected industries. We believe that a sector–based analysis of herding behaviour could reveal the true behavioural patterns among the various investor–types across the respective sectors. To a large extent, barring a few exceptions, most of the empirical models of herding in the JSE employ the conventional methods. To the best of our knowledge, no other studies have applied Bayesian linear regression models apart from the conventional approach in testing evidence of herding behaviour at the industry and sectoral levels. This study fills this void.

In this study, we offer three key contributions to the literature. First, as an alternative to the mainstream models, the study also extends the work of Chang, Cheng and Khorana (2000) by adopting the Bayesian linear regression to test evidence of herding behaviour. Secondly, we test evidence of herding behaviour in the entire financial industry and all sectors categorised under the industry. Lastly, the median is employed as an alternative measure for estimating the market return to minimise possible outlier effect in the calculation of the return dispersion metric. The study relates results and determines whether the alternative models lead to different conclusions with the conventional methods of analysis and the existence of the market phenomenon at the industry level and sectoral level.

The rest of the paper is outlined as follows. Section 2 describes the four methods of analysis. Section 3 defines the data and sample. Section 4 presents the empirical results. Section 5 concludes the paper.

2. METHODOLOGY

This part of the study describes and explains in details the methods employed in the analysis of the data. The method of analysis looks at the traditional approaches (i.e. cross–sectional standard deviation and cross–sectional absolute deviation) of testing herding behaviour and extends to the Bayesian regression model approach.

2.1. Evidence of Herding Behaviour: Traditional Approaches

Conventionally, testing evidence of herding behaviour has been analysed using two traditional metrics, namely the cross–sectional standard deviation and cross–sectional absolute deviation. To test evidence of herding behaviour in financial markets, the two methods primarily use dummy regression and OLS to investigate the relationship (i.e. linear/nonlinear) between return dispersion and market return. Both CSSD and CSAD have been used as dependent variables against market return, to examine herding behaviour of investors in the financial industry of the JSE.

2.1.1. Cross–Sectional Standard Deviation

Christie and Huang (1995) proposed the first technique, the cross–sectional standard deviation (CSSD) to test evidence of herding behaviour in financial markets. They posited that there exists a linear relationship between return dispersion and market return. Likewise, Chang, Cheng and Khorana (2000) suggested an alternative and advanced metric, the cross–sectional absolute deviation (CSAD) as a measure of return dispersion citing the CSSD as a technique that is sensitive to outliers. Unlike the CSSD, Chang, Cheng and Khorana (2000) suggested a non–linear relationship between return dispersion and market return. Both metric use the mean as a proxy to estimate market return. Return dispersion in the traditional framework is hence captured either by the CSSD or the CSAD approaches.

The median is a known robust measure of central tendency in the presence of outliers compared to the mean. For present purposes, we also consider the median as an alternative proxy to the mean in estimating market return. Employing both proxies for estimating market returns, the following regression model is run to examine the effect of market stress on individual return dispersion using the CSSD technique as formulated below.

$$CSSD = \alpha + \psi^{L} D_t^{L} + \psi^{U} D_t^{U} + \varepsilon_t \,, \qquad \textbf{(1)}$$

where D_t^L and D_t^U are dummy variables specifying the periods of market stress (bearish and bullish phases) from normal periods. ψ^L and ψ^U are the respective coefficients of the dummy variables to be estimated. α and ε_t represent the intercept and the noise respectively. The dummy variables in Eq. (1) are used as independent variables to differentiate the periods of market stress from normal periods. Next, the CSSD of return is regressed against two dummies (i.e. D_t^L and D_t^U), to specify and identify the extreme market phases. A market is characterised as stress when the aggregate market return lies within the upper or lower tails of the return distribution. So that, $D_t^L = 1$ if, on day t, $R_{m,t}$ lies in the lower tail of return distribution and 0 otherwise. Likewise, $D_t^U = 1$ if, on day t, $R_{m,t}$ lies in the upper tail of return distribution and 0 otherwise. We use the arbitrary 1%, 5% and 10% level thresholds for market stress.

Herding was proven if the dummy variables coefficients in Eq. (1) were negative and statistically significant. The return dispersion measure as prescribed by Christie and Huang (1995) is estimated as:

$$CSSD = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t} - r_{m,t})^2}{N-1}}, \qquad \textbf{(2)}$$

where $r_{i,t}$ is the return of stock i at time t and $r_{m,t}$ is the cross–sectional average (i.e. mean ($\bar{x}$) or median ($\tilde{x}$)) market return of N stocks of the sample at time t estimated using the arithmetic mean and the median respectively. During periods of extreme market stress, investors follow the market consensus rather than following their beliefs to seek certainty and conformity. This is to avoid making incorrect decisions which eventually leads to herding. In the presence of herding, investors' decisions are based solely on market movements and lead to individual asset returns moving in a similar direction to the overall market return. As a result, return dispersion estimated by CSSD turns to increase at a decreasing rate with increasing market returns. However, in the presence of severe herding, it may lead to a decrease in the return dispersion.

2.1.2. Cross–Sectional Absolute Deviation

The CSAD, an advanced measure of return dispersion is empirically determined as:

$$CSAD = \frac{\sum_{i=1}^{N} \left| r_{i,t} - r_{m,t} \right|}{N} , \quad \textbf{(3)}$$

where at time t, $r_{i,t}$, $r_{m,t}$ and N have the same meaning as previous.

A quadratic regression below is considered to test a nonlinear relationship between return dispersion and market return:

$$CSAD_t = \alpha + \eta_1 \left| r_{m,t} \right| + \eta_2 \, r_{m,t}^2 + \varepsilon_t , \quad \textbf{(4)}$$

where CSAD represents the return dispersion, α : the intercept, $r_{m,t}$: the market return; η_1 and η_2: regression estimates and ε_t: denotes the noise. Thus, the CSAD of return is regressed against both a linear and quadratic terms (i.e. $r_{m,t}$ and $r_{m,t}^2$), to identify and capture the nonlinear relationship between return dispersion and market return as suggested by Chang, Cheng and Khorana (2000). Under rational asset pricing model, η_1 is expected to be positive signifying the effect of stock exposures relating to the return dispersion measure (CSAD). To show evidence of herding behaviour, the coefficient of $r_{m,t}^2$ (i.e. η_2) is expected to be negative and statistically significant.

Market condition remains unstable, and hence stock behaviour may be asymmetric in the extreme market phases. Evidence of herding in the extreme tails of return distribution has been of particular interest to many stakeholders in the financial markets. To incorporate this market condition, the generalised relationship as indicated in Eq. (4) can be bifurcated into the following:

$$CSAD = \alpha + \eta_1^u \left| r_{m,t}^u \right| + \eta_2^u \, (r_{m,t}^u)^2 + \varepsilon_t , \quad \textbf{(5)}$$

$$CSAD = \alpha + \eta_1^d \left| r_{m,t}^d \right| + \eta_2^d \, (r_{m,t}^d)^2 + \varepsilon_t , \quad \textbf{(6)}$$

where CSAD and α have usual meaning as previous. $\left|r^{u}_{m,t}\right|$ and $\left|r^{d}_{m,t}\right|$ represent the market return in absolute terms when the market is rising (*u*) / falling (*d*). A negative and statistically significant values of η_2^u and η_2^d show evidence of herding behaviour.

2.2. Evidence of Herding Behaviour: Modern Approach

The current section describes an alternative model, the Bayesian linear regression of testing herding behaviour in financial markets. The proposed model extends the conventional CSAD approach where we investigate the nonlinear relationship between return dispersion and market return. As in the case of CSAD, we look for a statistically significant evidence of a nonlinear relationship between return dispersion and market return to prove herding behaviour.

2.2.1 Bayesian Regression

The traditional approaches as discussed above have been a central tool in testing herding behaviour in financial markets aimed at analysing the relationship between return dispersion (dependent variable) and market return (independent variable). In basic linear regression models where the expectation of the outcome simply equals the linear predictors have been expressed in different forms using different estimation methods such as (quasi–) likelihood, general estimation equation or Bayesian techniques.

Bayesian methodology is a unique approach that offers a realistic estimate of the model parameters. This is convenient since the inference is analytically tractable up to the covariance function parameters. This is as a result of the possibility to incorporate a prior knowledge about model parameters. In standard form, the likelihood has two parameters, the mean ($\beta = \beta_0, \beta_1, \beta_2$) and the variance ($\sigma^2$). In Bayesian linear regression analysis, the distribution of the response y is interpreted as a distribution of y given the parameters β and σ^2.

Eq. (4) can be stated in general form as;

$$y_i = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{m,t}^2 + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2) \tag{7}$$

$$y_i = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{m,t}^2 + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \kappa_t \sigma^2) \tag{8}$$

where y_i represents the dependent variable (i.e. return dispersion), β is a vector of β_0, the y – intercept, β_1, coefficient of the market return and β_2, the coefficient of the square of the market return. The error term (ε_i) is assumed to be normally distributed in Eq. (7) and t–distributed in Eq. (8) respectively.

Here, we consider two separate models, namely Model I and Model II. In Model I, represented by Eq. (7), the errors are assumed to be normally distributed while in Model II as shown in Eq. (8), the errors are t–distributed. Asset returns are not normally distributed and hence exhibit fat tails. Model II is considered to capture the tail behaviour adequately. This helps us to compare results in both scenarios.

Next, we choose conjugate prior distributions for the respective model parameters. In order not to put much emphasis on our prior knowledge, we choose the hyper-parameters in such a way that the priors are uninformative. The prior distributions and the corresponding posterior distributions are shown in Tables 1 and 2 for Model I and II respectively.

A step–by–step estimation of parameters in Eq. (7) and (8) are herein outlined. The Gibbs sampler algorithm is utilised to draw samples from the posterior distribution of the parameters in in Eq. (7) and (8). The Gibbs sampler procedure for Model I and Model II is described thusly:

Model I:

1. Initialise the parameters set $\Theta^{(0)} = (\beta_0^{(0)}, \beta_1^{(0)}, \beta_2^{(0)}, \sigma^{2(0)})$ where Θ denotes the set of all parameters we have in Model I.
2. For *k = 1* to *N* sweeps (where *N* is sufficiently large – at least 1000 sweeps)
   a. Update $\beta_0^{(k)} \mid \beta_1^{(k-1)}, \beta_2^{(k-1)}, \sigma^{2(k-1)}$
   b. Update $\beta_1^{(k)} \mid \beta_2^{(k-1)}, \sigma^{2(k-1)}, \beta_0^{k}$

c. Update $\beta_2^{(k)} \left| \sigma^{2(k-1)}, \beta_0^{(k)}, \beta_1^{(k)} \right.$

d. Update $\sigma^{2(k)} \left| \beta_0^{(k)}, \beta_1^{(k)}, \beta_2^{(k)} \right.$

Table 1: Posterior distributions of parameters in Model I

Parameters	Distribution	
Model I	**Prior**	**Posterior**
β_0	$\beta_0 \sim N(\mu_0, V_0)$	$N\left(B_0/A_0, 1/A_0\right)$
		$A_0 = \frac{1}{V_0} + \frac{N}{\sigma^2}$, $B_0 = \frac{\mu_0}{V_0} + \frac{\sum y_t - \beta_1 X_{1t} - \beta_2 X_{2t}}{\sigma^2}$
β_1	$\beta_1 \sim N(\mu_1, V_1)$	$N\left(B_1/A_1, 1/A_1\right)$
		$A_1 = \frac{1}{V_1} + \frac{\sum X_1^2}{\sigma^2}$, $B_1 = \frac{\mu_1}{V_1} + \frac{\sum X\,(y_t - \beta_0 - \beta_2 X_2)}{\sigma^2}$
β_2	$\beta_2 \sim N(\mu_2, V_2)$	$N\left(B_2/A_2, 1/A_2\right)$
		$A_2 = \frac{1}{V_2} + \frac{\sum X_2^2}{\sigma^2}$, $B_2 = \frac{\mu_2}{V_2} + \frac{\sum X_2\,(y_t - \beta_0 - \beta_1 X_1)}{\sigma^2}$
σ^2	$\sigma^2 \sim IG\,(\upsilon/2, \upsilon/2)$	$IG\left(a_0, b_0\right)$
		$a_0 = \frac{\upsilon + N}{2}$, $b_0 = \upsilon + \sum \left(y_t - \beta_0 - \beta_1 X_1 - \beta_2 X_2\right)^2$

Note: The table displays the posterior distributions of parameters with normally distributed errors. N (.), G (.) and IG (.) denote normal distribution, gamma distribution and inverse distribution respectively.

Model II:

1. Initialise the parameters set $\Theta^{(0)} = (\beta_0^{(0)}, \beta_1^{(0)}, \beta_2^{(0)}, \sigma^{2(0)}, \xi)$ where Θ denotes the set of all parameters we have in Model II.
2. For *k = 1* to *N* sweeps (where *N* is sufficiently large – at least 1000 sweeps)
   a. Update $\beta_0^{(k)} \left| \beta_1^{(k-1)}, \beta_2^{(k-1)}, \sigma^{2(k-1)}, \xi^{(k-1)} \right.$
   b. Update $\beta_1^{(k)} \left| \beta_2^{(k-1)}, \sigma^{2(k-1)}, \xi^{(k-1)}, \beta_0^{k} \right.$
   c. Update $\beta_2^{(k)} \left| \sigma^{2(k-1)}, \xi^{(k-1)}, \beta_0^{(k)}, \beta_1^{(k)} \right.$
   d. Update $\sigma^{2(k)} \left| \xi^{(k-1)}, \beta_0^{(k)}, \beta_1^{(k)}, \beta_2^{(k)} \right.$
   e. Update $\xi^{(k-1)} \left| \beta_0^{(k)}, \beta_1^{(k)}, \beta_2^{(k)}, \sigma^{2(k)} \right.$

Table 2: Posterior distributions of parameters in Model II

Parameters	Distribution

Model II	Prior	Posterior
β_0	$\beta_0 \sim N(\mu_0, V_0)$	$N\left(B_0^*/A_0^*, 1/A_0^*\right)$
		$A_0^* = \frac{1}{V_0} + \frac{N}{\sigma^2}$, $B_0^* = \frac{1}{V_0} + \frac{\sum y_t - \beta_1 X_{1t} - \beta_2 X_{2t}}{\sigma^2}$
β_1	$\beta_1 \sim N(\mu_1, V_1)$	$N\left(B_1^*/A_1^*, 1/A_1^*\right)$
		$A_1^* = \frac{1}{V_1} + \frac{\sum \kappa_t X_1^2}{\sigma^2}$, $B_1^* = \frac{\mu_1}{V_1} + \frac{\sum \kappa_t X_1 (y_t - \beta_0 - \beta_2 X_2)}{\sigma^2}$
β_2	$\beta_2 \sim N(\mu_2, V_2)$	$N\left(B_2^*/A_2^*, 1/A_2^*\right)$
		$A_2^* = \frac{1}{V_2} + \frac{\sum \kappa_t X_2^2}{\sigma^2}$, $B_2^* = \frac{\mu_2}{V_2} + \frac{\sum X_2 (y_t - \beta_0 - \beta_1 X_1}{\sigma^2}$
σ^2	$\sigma^2 \sim IG(\upsilon/2, \upsilon/2)$	$IG\left(a_0^*, b_0^*\right)$
		$a_0^* = \frac{\upsilon + N}{2}$, $b_0^* = \upsilon + \sum \kappa_t \left(y_t - \beta_0 - \beta_1 X_1 - \beta_2 X_2\right)^2$
ξ	$\kappa_t \sim IG\left(\frac{\xi}{2}, \frac{\xi}{2}\right)$, $\xi \sim Ga\ (a, b)$	$\xi^{\alpha-1} e^{-b\xi} e^{-\frac{\xi}{2}\sum \kappa_t} \prod_{t=1}^{N} \kappa_t^{\frac{\xi}{2}-1}$

Note: The table displays the posterior distributions of parameters with t–distributed errors. N (.), G (.) and IG (.) denote normal distribution, gamma distribution and inverse distribution respectively.

3. DATA AND SAMPLE

This section briefly describes the data used in testing evidence of herding behaviour in the financial industry of the JSE. Christie and Huang (1995) and Tan *et al*. (2007) recommend the use of high-frequency data in testing evidence of herding behaviour in financial markets. According to the authors, the market characteristic is often a short–term phenomenon and becomes more evident with daily data than weekly or monthly data. Hence, this paper uses daily return data to test evidence of herding behaviour in the JSE. We estimate the stock return r_t of all listed companies in the financial industry as:

$$r_t = 100 * [\ln(p_t) - \ln(p_{t-1})] \qquad \textbf{(11)}$$

Stock price data was obtained from McGregor Enert Expert Database and spanned the period from January 4, 2010, to 30 September 2015, leading to a sample of 1435 observations. The South African financial industry comprises five key sectors namely: banking, general financials, real estate, life insurance and non–life insurance respectively. Except for non–life insurance sector, the number of listed companies during the study period in each sector was at least two. Hence, we limit the sectors, into four by merging life insurance and non–life insurance as insurance.

4. RESULTS AND DISCUSSION

This part of the study presents the results as well as extensive discussion of empirical findings.

4.1 Descriptive Statistics

Table 3a presents observations of market return within the predefined market stress threshold of all sectors in the financial industry as well as the industry as a whole. Initial examination of the data in Table 3 shows a balanced number of observations based on the mean ($\bar{x}$) and the median ($\tilde{x}$). However, as the market stress threshold widens, the median market return decreases sharply as compared to the mean counterpart which leads to an insufficient number of observations. This may cause estimation problems leading to spurious results as a consequence of the lack of adequate observation for the analysis. Market stress threshold is defined subjectively. However, optimum care must be taken in ensuring that the number of observations is enough to be subjected to critical empirical analysis.

As it can be observed in Table 3a, the market stress threshold as defined using the median show fewer (less than 30) observations in comparison to the mean. This is more pronounced in the general financials and real estate sectors of the financial industry. The two sectors recorded at most twenty-four (24) observations in all market stress threshold especially using the median as a measure of market return. Even though the median is a robust measure of central tendency, it suffers from the lack of sufficient observations especially within the extreme tails of the market return distribution.

Table 3a: Average market return and threshold

Threshold	**Observations**									
	Banking		**Gen. Financials**		**Insurance**		**Real Estate**		**Fin. Industry**	
	$\bar{x}$	$\tilde{x}$	$\bar{x}$	$\tilde{x}$	$\bar{x}$	$\tilde{x}$	$\bar{x}$	$\tilde{x}$	$\bar{x}$	$\tilde{x}$
> 99%	15*	14*	15*	14*	15*	15*	14*	14*	15*	15*
< 1%	15*	15*	15*	14*	15*	15*	15*	8*	15*	15*
> 95%	72	72	72	22*	72	72	72	14*	72	37
< 5%	72	71	72	24*	72	69	72	8*	71	48
> 90%	144	142	144	22*	143	142	141	14*	143	37
< 10%	143	143	143	24*	144	140	143	8*	142	48
Whole	1435	1435	1435	1435	1435	1435	1435	1435	1435	1435
Companies	5		39		10		17		71	

Note: This table displays the number of observations below and above the extreme tails of market return distributions (mean ($\bar{x}$) and median ($\tilde{x}$)). * represents lack of sufficient number of observations.

Table 3b, on the other hand, displays the market return statistics of all sectors and the industry as a whole. Employing the mean ($\bar{x}$) proxy, except the real estate sector and the entire industry which exhibited positive skewness, the remaining sectors were found to be slightly skewed to the left. Thus, the market return is close to bell–shape but slightly skewed on both sides. Similarly, the market return distribution using the median ($\tilde{x}$) proxy showed negative skewness (slightly). However, the general financials sector, the real estate sector and the entire industry exhibited high negative skewness. Next, the kurtosis of all sectors and the aggregate market were found to be leptokurtic (kurtosis > 3). Thus, the market return distribution is symmetrical in shape; however, the center peak is much higher depicting higher frequency values.

Table 3b: Market return statistics

SECTOR	Proxy	Descriptive Statistics				
		min	**sd**	**skewness**	**kurtosis**	**max**
Banks	Mean ($\bar{x}$)	-0.05	0.01	-0.04	4.32	0.05
	Median ($\tilde{x}$)	-0.06	0.01	-0.05	4.48	0.05
General Financials	Mean ($\bar{x}$)	-0.07	0.01	-0.35	13.49	0.07
	Median ($\tilde{x}$)	-0.02	0.00	-6.99	212.41	0.01
Insurance	Mean ($\bar{x}$)	-0.03	0.01	-0.09	5.27	0.04
	Median ($\tilde{x}$)	-0.03	0.01	-0.07	7.37	0.04
Real Estate	Mean ($\bar{x}$)	-0.28	0.02	0.12	162.58	0.29
	Median ($\tilde{x}$)	-0.01	0.00	-2.32	230.47	0.01
Financial Industry	Mean ($\bar{x}$)	-0.06	0.01	0.10	20.47	0.08
	Median ($\tilde{x}$)	-0.02	0.00	-3.40	92.43	0.01

Note: This table displays the average market return statistics employing the mean and median as a measure of central tendency.

In all, seventy–one (71) financial industry companies were considered comprising four sectors, namely: banking (5), general financials (39), insurance (10) and real estate (17). The insurance sector is made up of two sectors, namely the life insurance and the non–life insurance.

4.2. Herding Behaviour in the Financial Industry: Sectoral Analysis

The current section presents the empirical findings of herding behaviour in all sectors categorised under the financial industry using the traditional (cross–sectional standard deviation and cross–sectional absolute deviation) and modern (Bayesian regression) approach.

4.2.1. Traditional Approach of Testing Herding Behaviour

Table 4 presents the empirical results of testing herding behaviour in the financial industry of the JSE using traditional and a modern method. In the traditional framework, CSSD shows evidence of herding behaviour only in the general financials sectors employing the mean as market return proxy. The result suggests that investors in the general financial sector follow the market consensus normal market periods. Thus, there was no evidence of herding during extreme market periods.

Similarly, we found evidence of herding behaviour in some sectors of the financial industry using the CSAD method. In the banking sector, we found evidence of herding behaviour only during the period when market return falls below the 10% threshold. This result is consistent using the two proxies for estimating market return. The coefficient of market return $r_{m,t}^2$ ($\eta_2\,(\bar{x}) = -9.4038$ and $r_{m,t}^2$ ($\eta_2\,(\tilde{x}) = -5.4213$) was found to be negative and statistically significant at a 10% significance level. The result implies that investors in the banking sector only herd when the market is falling (bearish phase).

Unlike the banking sector, however, investors in the general financials and real estate sectors only herd during the normal market period when the market is neither in the bearish (falling) nor bullish (rising) phase. In both sectors, we found evidence of herding behaviour using the median proxy only. The mean proxy in both cases failed to show any proof of the behavioural bias. Likewise, while the coefficient of market return $r_{m,t}^2$ ($\eta_2\,(\tilde{x}) = -87.4454$) in the general financials sector was found to be significant at a 10% significance level, in the real estate sector, it was found to be -8.2400 at a 1% significance level.

The insurance sector remains the only sector that showed no evidence of herding behaviour in the CSAD setup. No evidence of herding behaviour was found during normal and periods when the market was either falling or rising. None of the coefficients of $r_{m,t}^2$ was found to be statistically significant even though negative estimates were recorded in some cases. Thus, investors in the insurance sector exhibited no evidence of herding behaviour and hence invested in a rational manner.

4.2.2. Modern Approach of Testing Herding Behaviour

The alternative method of testing for herding behaviour in this study also shows inconsistent results in comparison with the traditional methods of the existence of the behavioural bias in all sectors. Results of the Bayesian regression model show virtually different results. In both models (i.e. Model I and II) in the Bayesian setup, we found no evidence of herding behaviour in all sectors during all market conditions. It can be observed in Table 4 that none of the credible intervals excluded zero in cases where the estimates were negative. The result suggests that investors in all the sectors were immune to the behavioural bias of herding and hence invested in a rational manner.

In brief, the results so far show that it is difficult to capture the herding behaviour using Bayesian linear regression model at the sectoral level. Whereas CSSD and CSAD methods captured the herding phenomenon in three sectors of the financial industry, the Bayesian linear regression failed to show any proof of the market phenomenon in all the sectors. Consistently, there was no evidence of herding behaviour applying all models in the insurance sector.

Table 4: Empirical results of test of herding behaviour by sector

SECTOR	Threshold	Traditional Approaches				Modern Approach			
		CSSD		CSAD		Bayesian Regression			
						Model I		Model II	
		$\psi(\bar{x})$	$\psi(\tilde{x})$	$\eta_2(\bar{x})$	$\eta_2(\tilde{x})$	$\beta_2(\bar{x})$	$\beta_2(\tilde{x})$	$\beta_2(\bar{x})$	$\beta_2(\tilde{x})$
BANKING	> 99%	0.0057***	0.0047***	- 50.5570.	15.618	0.0944	0.3671	-0.0992	-0.0149
		4.51	3.46	-2.05	1.25	- 16.23, 16.37	- 15.91, 16.56	- 16.42, 16.54	- 16.35, 16.38
	< 1%	0.0036**	0.0038**	0.5693	16.2751	0.061	0.4708	-0.0614	-0.0392
		2.85	2.75	0.02	0.86	- 16.27, 16.31	- 15.77, 16.70	- 16.44, 16.48	- 16.48, 16.34
	< 5%	0.0040***	0.0026***	-2.6243	-2.2015	-1.0041	-1.2001	-0.2187	-0.0938
		6.95	4.08	-0.32	-0.47	- 13.93, 11.92	- 12.39, 10.02	- 16.55, 16.02	- 16.15, 16.25
	> 95%	0.0037***	0.0029***	-3.7585	-7.9167	-1.5149	-4.3681	-0.2443	-0.2243
		6.36	4.67	-0.43	-1.72	- 14.37, 11.28	- 15.29, 6.59	- 16.47, 16.06	- 16.44, 15.87
	> 90%	0.0026***	0.0022***	-6.8534	1.2798	-1.0041	1.0269	-0.5881	-0.3898
		6.09	4.72	-1.56	0.39	- 13.93, 11.92	- 6.31, 8.37	- 16.57, 15.21	- 16.27, 15.48
	< 10%	0.0024***	0.0020***	**- 9.4038***	**- 5.4213***	-6.8127	-4.5717	-0.8660	-0.68
		5.70	4.34	**-2.04**	**-2.07**	- 15.43, 1.79	- 11.17, 2.06	- 16.65, 15.17	- 16.60, 15.27
	Whole	-0.0004	0.0007	0.8485	0.7573	3.2049	2.2351	14.3684	11.662
		-0.04	0.06	0.96	1.06	2.56, 3.85	1.70, 2.77	9.44, 19.36	7.22, 16.25
GEN. FINANCIALS	> 99%	0.1503***	0.0026	-9.3934	-88.0395	-1.108	-0.0581	0.0098	0.099
		23.33	0.28	-0.21	-0.54	- 16.86, 14.56	- 16.52, 16.31	- 16.07, 16.25	- 16.25, 16.60
	< 1%	0.1796***	0.0129	17.5846	-2.337	2.6099	-0.1955	-0.0348	0.0029
		27.87	1.38	15.52	-1.26	- 12.74, 17.78	- 16.71, 16.20	- 16.31, 16.52	- 16.55, 16.55
	< 5%	0.0626***	0.0006	-1.399	-74.4759	-0.9452	-0.1517	0.0705	-0.0095
		18.46	0.08	-0.26	-0.73	- 9.89, 7.99	- 16.66, 16.31	- 15.80, 16.13	- 16.33, 16.46
	> 95%	0.0692***	0.0058	5.2438	-1.358	3.2694	-0.7773	-0.4588	-0.0185
		20.39	0.78	0.76	-1.68	- 7.02, 13.50	-17.19, 15.53	- 16.25, 15.22	- 16.46, 16.41
	> 90%	0.0403***	0.0006	3.0742	-74.4759	2.643	-0.1143	-0.2632	0.1139
		15.03	0.08	0.84	-0.73	- 3.71, 8.96	- 16.51, 16.28	- 15.26, 14.63	- 16.40, 16.51
	< 10%	0.0406***	0.0058	1.001	-1.358	0.8011	-0.7277	-1.2154	-0.1686
		15.17	0.78	0.24	-1.68	- 6.17, 7.77	- 17.10, 15.66	- 15.99, 13.32	- 16.38, 16.56
	Whole	**- 0.2275***	-0.5887	1.3400***	**- 87.4454***	33.3353	9.2379	36.2217	5.0383
		-2.24	-0.57	12.55	**-1.98**	32.27, 34.40	- 5.71, 24.19	32.92, 41.08	- 11.44, 21.85
INSURANCE	> 99%	0.0313***	0.0052*	-691.591	- 42.9036.	0.7209	-0.4278	0.0017	-0.0547
		13.84	2.05	-1.34	-1.85	- 15.80, 17.07	- 16.74, 15.95	- 16.33, 16.34	- 16.58, 16.57
	< 1%	0.0203***	0.0078**	-647.8968	73.1526	-0.132	0.1552	0.0756	0.1078
		8.98	3.04	-1.70	0.86	- 16.56, 16.12	- 16.34, 16.45	- 16.32, 16.77	- 16.39, 16.43
	< 5%	0.0137***	0.0055***	18.1081	4.1812	1.86	1.1668	0.1044	-0.196
		12.89	4.56	0.69	0.39	- 13.73, 17.55	- 12.71, 15.06	- 16.40, 16.52	- 16.63, 16.03
	> 95%	0.0096***	0.0038**	-11.847	20.8001	-0.49	2.2533	-0.0256	-0.0088
		9.01	3.19	-0.31	1.28	- 16.57, 15.48	- 13.37, 17.69	- 16.65, 16.38	- 16.32, 16.36
	> 90%	0.0095***	0.0041***	23.3703.	-2.8562	7.8005	-1.6822	0.1444	-0.6495
		12.13	4.62	1.84	-0.45	- 5.59, 21.21	- 12.24, 8.84	- 16.19, 16.29	- 16.94, 15.47
	< 10%	0.0069***	0.0030***	15.5663	5.5049	-0.49	2.0242	-0.2295	-0.2751
		8.82	3.41	0.90	0.53	- 16.57, 15.48	- 11.13, 15.09	- 16.63, 16.26	- 16.52, 15.83
	Whole	0.0703*	0.0123	1.7210***	-2.4248	23.0673	10.321	42.3931	26.93
		2.24	0.33	7.88	-1.20	21.50, 24.63	8.77, 11.88	33.58, 50.57	17.69, 35.70
REAL ESTATE	> 99%	0.2042***	0.1744***	1.0491	-3.461	1.05	0.0661	0.4659	0.0146
		16.98	8.88	1.19	-0.96	- 1.72, 3.7546	- 16.38, 16.40	- 11.11, 11.85	- 16.46, 16.24
	< 1%	0.2209***	-0.0022	2.2173***	247.073	2.1882	0.2752	0.5102	-0.1381
		17.75	-0.15	4.68	2.18	- 0.17, 4.52	- 16.06, 16.72	- 11.61, 12.41	- 16.45, 16.72
	< 5%	0.1042***	0.1744***	1.0664*	-3.461	1.0658	-0.0906	-0.0135	0.008
		19.05	8.89	2.26	-0.96	0.188, 1.94	- 16.51, 16.33	- 5.26, 5.15	- 16.65, 16.34
	> 95%	0.1060***	-0.0022	1.1645**	247.0730.	1.1668	0.2556	0.1353	0.0547
		19.39	-0.15	2.83	2.18	0.38, 1.94	- 16.18, 16.64	- 4..97, 4.95	- 16.35, 16.40
	> 90%	0.0682***	0.1744	0.4253	-3.461	0.426	-0.0266	0.0371	0.1005
		16.12	8.89	1.48	-0.96	- 0.09, 0.94	- 16.57, 16.50	- 3.50, 3.67	- 16.52, 16.40
	< 10%	0.0707***	-0.0022	0.6930*	247.073	0.6925	0.187	0.181	0.0896
		16.61	-0.15	2.57	2.18	0.20, 1.19	- 16.22, 16.70	- 3.34, 3.69	- 16.34, 16.42
	Whole	-0.0368	7.9909**	0.6044***	**- 8.2400*****	6.9532	4.462	0.4912	290.0315
		-0.39	3.27	6.7	**-4.07**	6.75, 7.16	- 11.81, 20.75	- 4.23, 5.43	- 3770.10, 5743.65

Note: This table displays the result of four models of testing for evidence of herding behaviour within the four sectors of the financial industry (JSE). Values in red (bold) with *****, ****** and ******* denote evidence of herding behaviour at **10%**, **5%** and **1%** significance levels.

4.3. Herding Behaviour in the Financial Industry as a Whole: An Industrial Analysis

We present the findings of herding behaviour in the entire financial industry by aggregating all sectors as one market. In the previous section, the sectoral analysis of the financial industry showed evidence of herding behaviour in three sectors (i.e. banking, general financials and real estate) out of the four (4) sectors considered. In recent decades, several works have studied the market characteristics at the market level without much focus on the sectors. In most studies, researchers have focused predominantly on testing for evidence of herding behaviour based on a particular financial market as a whole or selected industries without much emphasis on the sectors categorised thereof. In this study, we proceed to perform a similar examination of the financial industry as a whole if herding behaviour was a market characteristic during the study period.

4.3.1. Traditional Approach for Testing Herding Behaviour

Table 5 shows empirical CSSD result for the financial industry as a whole. From the results, it is evident that none of the coefficients was statistically significant considering both the mean and the median with respect to CSSD. Both proxies, however, showed consistent results.

On the other hand, using the CSAD approach, we found evidence of herding behaviour during market days when the average market return falls below the 5% and above 90% threshold respectively. Evidence of herding behaviour in the financial industry also holds considering the entire industry. The results suggest that investors in the industry do not only herd during the normal market period but also exhibit the behaviour during periods of market stress. The results were only valid for the mean.

Consistently, CSSD results have shown no evidence of herding behaviour at the entire financial industry. This finding reaffirms the notion that it is difficult to capture the herding behaviour, especially with the CSSD method. Unlike CSSD, the CSAD captured the market phenomenon at the sectoral level as well as the entire industry.

Table 5: Empirical results of test of herding behaviour in the financial industry (JSE)

SECTOR	Threshold	Traditional Approaches				Modern Approach			
		CSSD		CSAD		Bayesian Regression			
						Model I		Model II	
		$\psi(\bar{x})$	$\psi(\tilde{x})$	$\eta_2(\bar{x})$	$\eta_2(\tilde{x})$	$\beta_2(\bar{x})$	$\beta_2(\tilde{x})$	$\beta_2(\bar{x})$	$\beta_2(\tilde{x})$
FINANCIAL INDUSTRY	**> 99%**	0.1096***	0.0016	209.9674**	-325.6227	-3.1485	-0.0855	-1.469	0.057
		15.1	0.18	3.79	-0.73	-19.22, 12.89	-16.49, 5.79	-18.75, 15.05	-16.58, 16.63
	< 1%	0.1476***	0.0000	-63.6566	130.8275	-2.3207	0.1094	-0.6952	-0.0563
		20.33	0.01	-1.53	0.35	-18.50, 13.84	-16.20, 16.54	-17.85, 15.64	-16.51, 16.41
	< 5%	0.05153***	0.0091.	**-33.6434***	-77.7034	-11.0275	0.0294	**-45.5414**	-0.2611
		14.24	1.83	**-2.51**	-0.18	-24.46, 2.61	-16.41, 16.45	**-77.77, -8.17**	-16.70, 16.28
	> 95%	0.0535***	0.0015	-16.5193	-99.9024	-3.6738	-0.4598	**-41.9933**	-0.2828
		14.88	0.28	-0.94	-0.68	-18.12, 10.77	-16.89, 16.00	**-78.55, -6.11**	-16.81, 16.11
	> 90%	0.0318***	0.0091.	**-33.8498***	-77.7034	**-18.8877**	-0.0143	**-131.3144**	-0.2763
		11.52	1.83	**-3.97**	-0.18	**-29.86, -7.87**	-16.38, 16.31	**-153.63, -121.35**	-16.71, 16.31
	< 10%	0.0330***	0.0015	-11.0492	-99.9024	-4.2339	-0.3884	**-163.6467**	-0.179
		12.01	0.28	-0.92	-0.68	-16.92, 8.56	-16.78, 15.95	**-193.79, -144.37**	-16.71, 16.20
	Whole	-0.1462	0.5189	**-0.7999**	-2.5320*	68.1066	8.3443	**-158.491**	-0.2134
		-1.14	0.65	**-0.23**	-2.37	63.88, 72.33	-7.93, 24.37	**-176.378, -131.93**	-16.55, 16.31

Note: This table displays the results of four models of testing for evidence of herding behaviour in the financial industry (JSE). Values in red (bold) with *****, ****** and ******* denote evidence of herding behaviour at **10%**, **5%** and **1%** significance levels.

4.3.2. Modern Approach to Testing Herding Behaviour

The results in Table 5 further showed that aggregating the sectors as a composite industry yield inconsistent results as compared to the results of the sectoral analysis. Again, this suggests that testing evidence of herding behaviour at the composite market may not show the true behaviour of investors. A bottom–up approach where each sector categorised under a financial market and tested for the behavioural bias may provide an in–depth insight into the behavioural dynamics of investors in a particular market.

In contrast to the sectoral analysis where results of the Bayesian linear regression failed to show any proof of herding behaviour in all sectors, results for the aggregate market show evidence of the behavioural bias. In Model I, results show evidence of herding behaviour when the market return falls above the 90% threshold using the mean proxy. However, it was absent in the entire market. This evidence sufficiently confirms that investors in the financial industry conduct their investment decision–making process in a rational manner but become irrational during the bull market phase.

On the other hand, we found evidence of herding behaviour in the bear and the bull market periods in Model II. Contrary to the previous results in the Bayesian framework at the sectoral level, these results suggest that investors in the financial industry exhibit the behavioural bias. Thus, investors disregard their beliefs and strategies in their investment decision–making process by following the market consensus during periods of market stress.

5. CONCLUSION

In this paper, we have examined herding behaviour of market participants in the Johannesburg Stock Exchange at both the sector and industry level from January 2010 to September 2015. The study employed the median as an alternative proxy in estimating market return. Apart from the Bayesian regression model, the empirical results of the sectoral analysis showed evidence of herding behaviour in the banking, general financials and real estate sectors. Except for the CSSD model, considering the financial industry as a whole, the empirical CSAD and the Bayesian linear regression results showed evidence of herding behaviour in the entire industry. Largely, it can be concluded that investors in the financial industry exhibited the behavioural bias in the study period

The study showed a significant nonlinear relation between return dispersion as captured by CSAD and market return in the banking, general financials and real estate sectors. The findings in this study are consistent with the results of other researchers such as Chang *et al.* (2000); Lao and Singh (2011); Economou *et al*. (2011) who observed that the characteristics of an emerging market make herding behaviour more likely in comparison with advanced markets. Lack of evidence of herding behaviour in the insurance sector in the same industry also contradicts this notion. On the other hand, the findings of the current study further support the evidence of herd behaviour on the JSE by similar studies (Gilmour and Smit (2002); Seetharam and Britten (2013); Sarpong and Sibanda (2014)). The use of the median proxy showed comparable results with the arithmetic mean. However, it posed severe data problem in the extreme tails of the market distribution. Hence, one must take care when subjectively choosing a market stress threshold

In conclusion, we emphasise the importance of testing evidence of herding behaviour not only at the market or industry level but also at the sector level. Testing herding behaviour at the level of an industry or sector may fail to unravel the true behavioural dynamics in a financial market as shown in this study.

Further research could investigate the essential characteristics of financial markets susceptible to the herding behaviour as evidence from studies in both advanced, and emerging markets have yielded inconsistent results using different techniques. It could be interesting to test evidence of herding behaviour in other financial markets; first at market, industry and sectoral levels and secondly, compare results in both markets using alternative estimating methods.

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