Investor Herd Behaviour in Africa's Emerging and Frontier Markets

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ABSTRACT

Daily returns of 224 stocks traded on three distinctively classified markets (stand-alone, frontier, and emerging) within a developing continent context are used, employing the Chang, Chen and Khorana (2000) measure. We provide evidence of the presence of investor herding in Africa's emerging and frontier markets. Evidence of asymmetric herding activities during various market conditions is further provided. The paper also shows that the 2007-2009 global financial crisis did not intensify herding in African markets. The findings suggest that Africa's leading markets are still fairly inefficient, allowing for potential excess returns for investment strategies that seek to explore market anomalies.

Keywords: Behavioural Finance, Investor Behaviour, Herding, African Markets, Asymmetric Herding
JEL Classifications: G01, G10, G14, G15

1. INTRODUCTION

"Men nearly always follow the tracks made by others and proceed in their affairs by imitation."

Niccolo Machiavelli, The Prince, Ch. 6, 1514

Investors herd when they disregard their private information and follow the investment decisions and actions of others. Herding behaviour is a market anomaly and a phenomenon that is at variance with the efficiency market hypothesis (EMH). In the presence of herding, investors incur additional costs as financial markets become greatly destabilised. Investor herding in stock markets is thus a major subject of continuous global concern about excess volatility and spillover across international markets. For example, Blasco et al. (2012) report a direct linear effect of investor herding on volatility; Avramov et al. (2006) document strong evidence of the impact of both herding and contrarian investors on intraday volatility, and dating back in the 1980s and 1990s, Froot, et al. (1992) and Wang (1993) all support the

assertion that investor herding causes extreme price movements in financial markets.

Some empirical studies about herd behaviour have been conducted, albeit with mixed findings, in developed equity markets (Christie and Huang, 1995; Chang et al., 2000; Blasco et al., 2012; Bennet et al., 2015), emerging markets (Demirer and Ulussever, 2011; Chiang and Zheng, 2010; Yao et al., 2014), and frontier markets (Guney et al., 2016). Nonetheless, findings of studies of herding in Africa's emerging and frontier equity markets have not been communicated in exactitude. African studies mostly focus on the South African stock market (Niyitegeka and Tewari, 2015) or unit trust industry in South Africa (Gilmour and Smit, 2002). This gap in the literature thus begs the question "do investors herd in Africa's emerging and frontier stock markets? If herd behaviour is detected in the Africa's emerging and frontier markets, then, first that will provide further evidence against the efficiency of these markets. Second, it will imply that the efforts toward increasing globalisation and market integration with Africa's emerging and frontier markets and the rest of the world are yet to yield the desired results – for enhanced market integration and efficiency. Third,

that could also mean that stock markets in Africa may continue to provide diversification opportunities, although potential risks could be enormous. Such evidence would therefore have several policy and investment implications for the rest of the world, and in particular, for emerging and frontier markets, given that the African continent has become an important investment destination for governments and investors globally.

This view in relation to investor herd behaviour is very instructive, given that the validity of the efficient market hypothesis has been challenged and questioned. In fact, its theoretical foundations and empirical evidence have been sharply critiqued at the dawn of the twenty-first century. Criticisms include the fact that the EMH does not take into account investors' rationality and the presence of potential arbitrage opportunities. Investor rationality assumption suggests that market participants are rational and possess cognitive biases that influence their expectations and preferences over-time. Also, the fact that financial markets are constrained institutionally and structurally creates arbitrage opportunities for the informed and superior investor. Following from this, a number of market anomalies which create excess return opportunities for some investors have been identified in the literature (see Schwert, 2003 for a summary of the different types of anomalies and Alagidede, 2008 for an extensive review). It is therefore unlikely that all investors will earn homogenous returns from their investment decisions and strategies.

In the present study we investigate investor herd behaviour in Africa's emerging and frontier equity market using the cross-sectional absolute deviation measure (CSAD) proposed by Chang et al. (2000). The study also examines whether or not asymmetric herd behaviour can be detected under different market conditions (i.e. during rising, falling and volatile markets), and whether or not the 2007-2009 global financial crisis did intensify investor herd behaviour in Africa's emerging and frontier markets. This study thus follows the second strand of empirical research and tests herding towards the market-wide index. A number of factors, such as the investment horizon of investors, the benchmark for measuring performance, the behaviour of other market participants, the extent of underlying market volatility, and the occurrence of fads and speculative trading activities in the financial markets have been suggested as influencing investment behaviour (Chang et al., 2000). Definitely, herd behaviour in financial markets needs considerable research attention because of its perceived connection with price volatility, financial crisis, market inefficiency, and their policy implications.

The motivation for this study is threefold. First, awful policy implications are reported to be associated with investor herding. Specifically, investor herd behaviour is said to destabilise markets and increase the fragility of the overall financial system, including causing severe stock price movements (Tan et al., 2008) and producing widespread financial crises (Bikhchandani and Sharma, 2001). Thus the study of herd behaviour in Africa's emerging and frontier markets would help to explain market-wide anomalies in the African financial markets and inform the design of appropriate market-oriented policies to curtail it. Second, the unique features of the emerging and frontier markets in Africa qualify them as

an appropriate location to investigate investor herding. Until now no study has communicated with attitude evidence of herd behaviour in Africa's major financial markets. Some stylised facts about African financial markets include the fact that none is a developed market, few are emerging markets (Egypt, Morocco and South Africa), while the majority of them are frontier markets. The markets are also characterised by moderately high volatility, illiquid stocks, and weak regulatory standards and accounting reporting systems. As a result, herd behaviour has been proven to be widespread in emerging markets and pervasive under severe market conditions (Tan et al., 2008). Besides, African markets have witnessed increased foreign investor participation in recent times. The behaviour of some foreign investors is however to enter and exit emerging markets in herds, which can further engender market inefficiency and uncertainty. Third, most asset managers in African markets adopt active investment strategies in which "so called" superior technical analyses are implemented with a view to out-performing the market. These fund managers attempt to predict future security price movements in order to realise abnormal returns. This situation, nevertheless, is a breeding ground for herd behaviour, as lazy and self-centred fund managers may simply disregard their private information and initial investment decisions and imitate other fund managers. This behaviour converges with the belief that it is better to fail conventionally than to succeed defiantly (Scharfstein and Stein, 1990).

For the rest of the paper, Section 2 discusses the relevant literature, Section 3 describes the data and their statistical properties and methodology. Section 4 presents and discusses the results, while Section 5 provides the conclusions of the study.

2. RELATED LITERATURE REVIEW

Theoretical and empirical research on herd behaviour has been undertaken in rather isolated fashion (Wang, 2008). While theoretical studies focus on the causes and implications of herd behaviour (Scharfstein and Stein, 1991; Bikhchandani et al., 1992; Welch, 1992), empirical studies typically attempt to measure the presence of herding in a purely statistical sense, and do not test any specific theoretical models of herding. The main consensus, nevertheless, is that herd behaviour can be construed as being either a rational or irrational form of investor behaviour (Chang et al., 2000). According to Devenow and Welch (1996), the irrational view emphasises investor psychology where investors ignore their private information and prior belief and blindly follow other investors. The rational view, on the contrary, focuses on the principal-agent problem in which institutional investors such as fund managers completely disregard their private information and imitate the actions of others for purposes of maintaining their reputational capital in the financial markets (Scharfstein and Stein, 1990; Froot et al., 1992; Rajan, 1994). Bikhchandani et al. (1992) and Welch (1992) describe this investor behaviour as an informational cascade which can lead to wrong investment decisions for all investors in the herd. The rational form of investor behaviour may not however apply to individual investors since most individual investors are anonymous (Chen et al., 2003). Bikhchandani and Sharma (2001) and Kremer and Nautz (2012) refer to the consensus as herding types which can be either

sentiment-driven intentional herding or unintentional (spurious) herding. The latter type of herding is driven by widespread identical response to public information and signals. In particular, intentional herding can destabilise security prices and impair the efficiency of financial markets (Scharfstein and Stein, 1990; Hirshleifer and Teoh, 2003; Hwang and Salmon, 2004). Kremer and Nautz (2012) argue that unintentional herd behaviour can also lead to market inefficiency if the correlated actions of market participants are not driven by fundamentals values. Thus, for all conceptual models on herd behaviour developed in the 1990s and beyond, investors are deemed to exhibit the tendency to herd on one side of the market.

On the empirical front, several studies have been conducted globally to test the presence of herd behaviour in financial markets. The literature either tests clustering of investors' decisions within a defined group in the market or examine herding at a broad market level (Wang, 2008). In a pioneering work on the first category, Lakonishok et al. (1992) measure herding as the average tendency of fund managers to buy (sell) contemporaneously the same stocks as other fund managers buy (sell), relative to what would have been expected had these managers executed their transactions independently. Using a sample of 769 equity funds, the study finds no evidence of herd behaviour among fund managers in the US financial markets. Grinblatt et al. (1995) apply the methods of Lakonishok et al. (1992) on the investment strategies of 155 mutual funds for the 1984-1994 period and find that 120 out of this sample were momentum traders. The study also documents evidence of high correlation between the tendency for a fund to herd in its investment decisions and its tendency to buy past winners (momentum stocks). Wermers (1995) suggests a portfolio-change measure of herding which measures the extent of clustering between portfolio weights assigned to various securities by fund managers.

The second strand of empirical research on herd behaviour adopts a market-wide approach which focuses on the collective behaviour of all market participants towards the market view, leading to a simultaneous purchase or sale of specific assets. In Christie and Huang (1995), the cross-sectional (market-wide) standard deviation of individual stock returns is regressed on a constant and a dummy variable that serves as a proxy for extreme positive and negative market returns. In their view, during periods of market stress (extreme price movements), a positive coefficient of the dummy variable would imply rational asset pricing, whereas a negative coefficient would suggest the presence of herding. It is worth noting that the Christie-Huang's study establishes the possibility of herding to be investigated using only stock price information instead of the rigorous task of obtaining detailed information of individual investment transactions. Extending the work of Christie and Huang (1995), Chang et al. (2000) specify a non-linear regression model to examine the relation between the level of stock return dispersion (measured as the cross-sectional absolute deviation, i.e. CSAD) and the overall market return. They argue that, in the presence of severe or moderate herd behaviour, the equity return dispersions would be expected to decrease (or increase at a decreasing rate) with an increase in market return. On the other hand, absence of herding in the market would imply that

periods of extreme price movements are associated with increase in equity return dispersions. Hwang and Salmon (2004) employ the cross-sectional dispersion of beta to test herding towards the market index. They authors attempt to distinguish herding from "spurious herding" which refers to a common movement of asset prices and returns resulting from movements in economic fundamentals and does not necessary cause market inefficiency. In essence, studies on the investment behaviour of financial market participants have surged because of the link between such behaviours and security price movements, and their implications for the proper functioning of financial markets.

3. METHODOLOGY AND DATA

The extant literature in this area of inquiry provides a number of alternative approaches to testing investor herd behaviour in capital markets. Prominent among these alternative methodologies are those by Lakonishok et al. (1992), Christie and Huang (1995), Chang et al. (2000), and Hwang and Salmon (2004). In this study, the methodology applied to investigate investor herd behaviour in Africa's emerging and frontier markets is the CSAD measure proposed by Chang et al. (2000), also known as the CCK model. The CCK model is mainly concerned with the relationship between equity return dispersions and market return. The prediction of the CCK model is that, the relationship between equity return dispersions and the absolute value of market return is decreasing and non-linear. While the CCK model concurs with the predictions of standard capital asset pricing models that equity return dispersions increase with market returns, the model also assumes a linear relationship between return dispersions and market return in normal market periods. Within equilibrium CAPM framework in the form consistent with Black (1972) and taking R_i to represent the return on a given security i, R_m being the market portfolio return and $E_t(\cdot)$ denoting the expectation in period t, the CCK model in its initial form is specified as follows:

$$\mathrm{E}_t\left(R_i\right) = \gamma_0 + \beta_i \mathrm{E}_t\left(R_m - \gamma_0\right) \tag{1}$$

where γ_0 is the return on the risk-free portfolio, β_i is the measure of time-invariant systematic risk of the security, $i = 1,\ldots\ldots,N$ and $t = 1,\ldots\ldots,T$. In the presence of herd behaviour however, CCK predict the disappearance of the positive and linear relationship between return dispersions and market expected return, giving way to a negative and non-linear relationship instead. Consequently, letting $CSAD_t$ and $R_{m,t}$ stand proxy for the unobservable variables $ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m|\mathrm{E}_t\left(R_m - \mathrm{Y}_0\right)$ and $E_t(R_{m,t})$, respectively, the CCK model is presented formally as follows:

$$CSAD_t = \gamma_0 + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{2}$$

where $CSAD_t$ is the average $AVD_t = |\beta_i - \beta_m| E_t(R_m - Y_0)$ of each security in relation to the equally-weighted market portfolio return, $R_{m,t}^2$ is the square of $R_{m,t}$, γ_0, γ_1 and γ_2 are parameters to be estimated, and ε_t is the error term. The values of $CSAD_t$ can be computed using $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|$, where $R_{m,t}$ is the average return

of an equally weighted market portfolio at period t, $R_{i,t}$ is the individual stock return of firm i at period t, with N being the number of firms. Accordingly, this proposition should capture any probable non-linear relationship between security return dispersions and the aggregate market return (Chang et al., 2000). It must be noted that CSAD in itself does not measure herding, but rather the relationship between $CSAD_t$ and $R_{m,t}$ is used to detect herd behaviour. The prediction is that in normal periods, the absolute market portfolio return $|R_{m,t}|$ increases resulting in an increase in $CSAD_t$ with γ_1 and γ_2 being positive and zero, respectively. Conversely, in periods of large market movements, investors become more apprehensive and the value of $CSAD_t$ declines (or increases at a decreasing rate) resulting in a significantly negative γ_2. This situation signals the presence of herd behaviour, but a significantly positive γ_2 is indicative of anti-herding behaviour or exaggeration of difference as the prevailing market conditions produce greater dispersion in stock returns (Tessaromatis and Thomas, 2009). In the absence of herding in equation (2), we anticipate $\gamma_1 > 0$ and $\gamma_2 = 0$, whereas in the presence of herding we anticipate a statistically significant $\gamma_2 < 0$.

The CCK model is also implemented in this study to test whether herd behaviour in the Africa's emerging markets can be said to intensify during periods of financial crisis. Indeed, herd behaviour has been found to be pronounced during periods of market stress (Balcilar et al., 2013; Mobarek et al., 2014; Galariotis et al., 2015). In particular, financial crisis has been found to trigger investor herding first in the crisis market, which is then subsequently propagated in other markets (Chiang and Zheng, 2010). As a result, the present study additionally tests whether the global financial crisis[1] in the 2007-2009 periods produced and intensified herding behaviour in Africa's stock markets. To accomplish this, the equation (2) is extended by including a dummy variable for the squared market return. Hence, the following equation is specified:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 D^{CRISIS} R_{m,t}^2 + \varepsilon_t \quad (3)$$

where D^{CRISIS} is the 2007-2009 global financial crisis dummy, taking the value of 1 on trading days during the crisis and 0 on all other days outside the crisis period. A significantly negative value of γ_3 is indicative of the presence of herd behaviour during the financial crisis period. Herd behaviour would be said to have intensified in the crisis period if $\gamma_3 > 1$ in absolute terms. A significantly positive value of γ_3 is an indication that the crisis period did not intensify herding in the stock markets.

3.1. Herding Asymmetry under Various Market Conditions

A number of empirical studies have found asymmetric herd behaviour in different market conditions (Garg and Gulati, 2013; Mobarek et al., 2014; Niyitegeka and Tewari, 2015). Motivated by the evidence, the present study also examines whether asymmetric herding behaviour can be detected in Africa's emerging markets during different market conditions relating to market returns, trading volume, and return volatility. Essentially, the goal here is to

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[1]   The global financial crisis covers the period 2007-2009 to take care of investors' apprehension during the sub-prime mortgage securities bubbles as well as any second round effect during the latter part of 2009.

test whether herd behaviour differs depending on whether market returns are positive or negative, whether trading volumes are high or low, and whether return volatility is high or low.

First, the asymmetric effects of market return are detected by testing whether the direction of market return (rising or declining markets) has an influence on the behaviour of market participants. These asymmetries are ascertained by estimating two separate regression equations, one for positive market returns and the other for negative market returns, specified as follows:

$$CSAD_t^{UP} = \gamma_0 + \gamma_1^{UP} \left| R_{m,t}^{UP} \right| + \gamma_2^{UP} \left(R_{m,t}^{UP} \right)^2 + \varepsilon_t \quad if\ R_{m,t} > 0 \quad (4)$$

$$CSAD_t^{DOWN} = \gamma_0 + \gamma_1^{DOWN} \left| R_{m,t}^{DOWN} \right| + \gamma_2^{DOWN}$$
$$\left(R_{m,t}^{DOWN} \right)^2 + \varepsilon_t \quad if\ R_{m,t} < 0 \quad (5)$$

where equation (4) denotes days of positive market returns while equation (5) represents days of negative market returns. The regressors $R_{m,t}^{UP}$ and $R_{m,t}^{DOWN}$ are the equally-weighted market portfolio returns at period t when the market rises and declines, respectively. The variables $CSAD_t^{UP}$ and $CSAD_t^{DOWN}$ are CSADs at periods corresponding to rising markets and declining markets, respectively. It is expected that in the presence of asymmetric herding behaviour during bullish and bearish markets, significantly negative parameters of γ_2^{UP} and γ_2^{DOWN} will be observed. A significantly more negative value of γ_2^{UP} (γ_2^{DOWN}) will be an indication that investor herding is more prevalent in bullish markets (bearish markets).

In an alternative, but CCK-modified estimation technique, Chiang and Zheng (2010) have found that investor herd behaviour is affected by the direction of market returns. Thus in the spirit of Chiang and Zheng and as a robustness check to the results in the present study, a revised CCK model is estimated. This is accomplished by including an additional term $R_{m,t}$ on the right-hand side of the original CCK model in equation (2) in order to allow for the detection of asymmetric herding under different market conditions. The modified CCK model is specified as follows:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \quad (6)$$

In equation (6), it can be shown that $\gamma_1 + \gamma_2$ captures the relation between return dispersions and market return when market is rising $R_{m,t} > 0$, whereas $\gamma_1 - \gamma_2$ indicates the relation between the two when market is falling $R_{m,t} < 0$. Also, the ratio of $\dfrac{\gamma_2 + \gamma_1}{\gamma_2 - \gamma_1}$ can be regarded as a measure of the relative amount of asymmetry between return dispersion and market return.

Second, the study also examines the asymmetric effects of trading volume by testing whether days of high and low trading volumes exhibit different investor behaviour and their tendency to herd around the market consensus. Following Tan et al. (2008), the trading volume V_t on day t is considered high if it is greater than

the previous 30 days' moving average. On the other hand, the trading volume V_t on day t is described as low if it is less than the prior 30 days' moving average. The possibility of the presence of these asymmetries is detected using the following specifications:

$$CSAD_t^{V-HIGH} = \gamma_0 + \gamma_1^{V-HIGH} \left| R_{m,t}^{V-HIGH} \right|$$
$$+ \gamma_2^{V-HIGH} \left(R_{m,t}^{V-HIGH} \right)^2 + \varepsilon_t \tag{7}$$

$$CSAD_t^{V-LOW} = \gamma_0 + \gamma_1^{V-LOW} \left| R_{m,t}^{V-LOW} \right|$$
$$+ \gamma_2^{V-LOW} \left(R_{m,t}^{V-LOW} \right)^2 + \varepsilon_t \tag{8}$$

Equations (7) and (8) respectively represent high and low trading volumes with $R_{m,t}^{V-HIGH}$ and $R_{m,t}^{V-LOW}$ being their corresponding equally-weighted market returns at period t when trading volumes are high and low. The variables $CSAD_t^{V-HIGH}$ and $CSAD_t^{V-LOW}$ represent CSADs at periods corresponding to high and low trading volumes, respectively. It is anticipated that in the presence of asymmetric herding behaviour during high and low volumes, significantly negative parameters of γ_2^{V-HIGH} and γ_2^{V-LOW} will be detected. Also, a significantly more negative value of γ_2^{V-HIGH} (γ_2^{V-LOW}) is suggestive of more prevalent herding behaviour during high trading volume (low trading volume).

In the third and final measure of herding asymmetry, the present study investigates whether herding behaviour varies depending on the degree of volatility in the market. Similar to the preceding analysis on trading volume, the volatility σ_t^2 of day t is described as high (low) if it is greater (less) than the prior 30 days' moving average. The possibility of the presence of herding asymmetries based on price volatility is detected using the specifications below:

$$CSAD_t^{\sigma^2 HIGH} = \gamma_0 + \gamma_1^{\sigma^2 HIGH} \left| R_{m,t}^{\sigma^2 HIGH} \right|$$
$$+ \gamma_2^{\sigma^2 HIGH} \left(R_{m,t}^{\sigma^2 HIGH} \right)^2 + \varepsilon_t \tag{9}$$

$$CSAD_t^{\sigma^2 LOW} = \gamma_0 + \gamma_1^{\sigma^2 LOW} \left| R_{m,t}^{\sigma^2 LOW} \right| + \gamma_2^{\sigma^2 LOW} \left(R_{m,t}^{\sigma^2 LOW} \right)^2 + \varepsilon_t \tag{10}$$

Equations (9) and (10) represent high and low volatility with $R_{m,t}^{\sigma^2 HIGH}$ and $R_{m,t}^{\sigma^2 LOW}$ being the corresponding equally-weighted market returns at period t during which volatility is high and low, respectively. The regressands $CSAD_t^{\sigma^2 HIGH}$ and $CSAD_t^{\sigma^2 LOW}$ respectively represent CSADs at periods of high and low volatility. The expectation is that the parameters $\gamma_2^{\sigma^2 HIGH}$ and $\gamma_2^{\sigma^2 LOW}$ will be significantly negative if asymmetric effects of herding exist, otherwise they do not exist. Moreover, if herd behaviour is more prevalent during high volatility compared to low volatility, the value of $\gamma_2^{\sigma^2 HIGH}$ must be more negative than the value of $\gamma_2^{\sigma^2 LOW}$.

3.2. Data and Preliminary Analysis

The daily closing prices and trading volumes of the most actively traded stocks in each of the considered stock exchanges retrieved from McGregor BFA are used in this study. The choice of daily frequency data was guided by evidence to the effect that herd behaviour is often a momentary phenomenon and is easily captured with high frequency data (Christie and Huang, 1995). Besides, evidence has shown that the detection of herding becomes more obvious with daily data than data with weekly and monthly frequency (Bhaduri and Mahapatra, 2013). Also, the use of the most liquid stocks is intended to help circumvent potential bias in the estimators that could arise due to thin trading (Brooks et al., 2006) which is a stylised fact about emerging and frontier market data. The data are all denominated in US dollar terms to ease comparison and all infrequently traded stocks were filtered out. The number of constituent firms used include 60 listed firms for South Africa, 58 firms for Egypt, 40 firms for Morocco, 36 firms for Kenya, and 30 firms for Nigeria. The sample periods differ across markets and are determined mainly by availability of quality data.

Prior to the analysis however, the daily closing prices were transformed into continuously compounded daily returns using the equation the below: $R_t = \left(lnS_t - lnS_{t-1} \right) \times 100 = \left(\dfrac{lnS_t}{lnS_{t-1}} \right) \times 100$,

where R_t is the continuously compounded daily closing stock return, lnS_t is the natural logarithm of day t or current day's closing share price, and lnS_{t-1} is the previous day's closing share price. Table 1 presents a summary of the descriptive statistics of the main variables of interest comprising the cross-sectional absolute deviation ($CSAD_t$), the weighted market return $R_{m,t}$, and the squared value of weighted market return $R_{m,t}^2$. The total observations for each of the considered stock markets are also reported and are generally large enough for the empirical analysis. From Table 1, the $CSAD_t$ and the squared value of weighted market return both exhibit a positive mean value for all five markets.

The lowest value of the $CSAD_t$ is observed in Kenya while the highest $CSAD_t$ is recorded in Morocco. The values of weighted market return are negative for all markets, except the South African stock market. Volatility as measured by the standard deviation appears fairly high for most variables in all markets. With the exception of the weighted market return $R_{m,t}$, the distributional properties of the variables of interest, as shown by the third and fourth moments (i.e. skewness and kurtosis) seem to exhibit extreme observations.

In particular, the $CSAD_t$ and $R_{m,t}^2$ are positively skewed for all the markets with generally large values of skewness. The skewness indicators for the weighted market returns are negative (except for Kenya) and <1 in all cases. Positive skewness is an indication that the distribution has an asymmetric tail that extends towards more positive values, while negative skewness shows a distribution with an asymmetric tail that extends towards more negative values. Thus the values of skewness suggest that most of the actual series of the $CSAD_t$ and $R_{m,t}^2$ variables are greater than their respective means, while the $R_{m,t}$ has actual values substantially smaller than the mean. Normally, investors prefer positively skewed return distribution over negatively skewed return distribution because

Table 1: Summary statistics for market returns and cross-sectional absolute deviation measure

Market/variable	Obser-vations	Mean (%)	SD (%)	Minimum (%)	Maximum (%)	Skew-ness	Kur-tosis	Jarque-bera Statistic
Egypt								
$CSAD_t$	1233	1.544	1.092	0.246	10.060	2.500	17.258	11729.09***
$R_{m,t}$	1233	−0.002	1.549	−0.572	10.450	−0.505	9.682	2346.01***
$R^2_{m,t}$	1233	2.398	7.069	0.000	118.21	8.619	112.57	632073.7***
Kenya								
$CSAD_t$	1661	1.416	0.875	0.834	13.952	7.665	96.673	623542.3***
$R_{m,t}$	1661	−0.014	0.977	−5.324	8.253	0.585	13.869	8270.12***
$R^2_{m,t}$	1661	0.953	3.416	0.000	68.104	10.875	161.56	1772810***
Morocco								
$CSAD_t$	1458	3.495	0.509	2.108	9.176	2.668	24.378	29495.87***
$R_{m,t}$	1458	−0.018	0.772	−3.787	2.811	−0.045	4.542	145.09***
$R^2_{m,t}$	1458	0.596	1.123	0.000	14.345	4.592	34.82	66643.27***
Nigeria								
$CSAD_t$	1661	2.537	1.243	0.765	23.647	11.233	184.86	2323907***
$R_{m,t}$	1661	−0.054	1.412	−8.919	6.396	−0.371	6.757	1015.070***
$R^2_{m,t}$	1661	1.996	4.810	0.000	79.555	7.395	88.052	515779.7***
South Africa								
$CSAD_t$	2346	1.454	0.686	0.562	7.201	2.084	10.284	6884.456***
$R_{m,t}$	2346	0.016	1.969	−12.85	12.889	−0.239	8.063	2528.104***
$R^2_{m,t}$	2346	3.878	10.304	0.000	166.14	8.419	102.98	1004821***

The samples comprise Egypt (09/02/2010-31/12/2014); Kenya (19/08/2008-31/12/2014); Morocco (29/05/2009-31/12/2014); Nigeria (19/08/2008-31/12/2014); and South Africa (03/01/2006-31/12/2014). ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively, while t-statistics are in parentheses

of relative risk aversion. Also, the substantially large values of kurtosis suggest that the daily returns distributions of the considered variables are leptokurtic (i.e. having slim and long-tailed distributions). The kurtosis is >3 for all variables and for all stock markets. Moreover, the Jarque-Bera test statistics and corresponding probability values reinforce the excess kurtosis and skewness measures, and thus suggest evidence against normal distribution for all the market returns.

4. RESULTS AND DISCUSSION

Prior to analysing the empirical results, the stationary properties of the return series were verified using the two classical unit root tests; the augmented Dickey-Fuller and Phillips-Perron. Table 2 presents the results of the unit root tests. Compelling results are observed as both the weighted market return and cross-sectional absolute deviation series were stationary at levels for all methods and for all countries. In the rare instances where some series are not stationary at level, they all turned to stationarity after first differencing. The results largely became more significant after the first differencing. The stationarity of the series means the existence of a stationary stochastic process containing constant mean and variance over time with a non-serially correlated covariance.

4.1. Herd Behaviour by the CSAD Measure
In the first part of the analysis, the CCK model (equation 2) was estimated and the results reported in Table 3. The results indicate evidence of the presence of herd behaviour in Africa's emerging markets. The herding coefficient γ_2 is negative and statistically significant at the 1% significance level for all the markets. In terms of cross-country comparison, the Moroccan and Nigerian stock markets exhibit the greatest intensity of herd behaviour followed by the stock markets in Kenya and Egypt. The South African stock market is perceived to exhibit

less herding behaviour (which to some extent is indicative of its degree of market efficiency). These results imply that the linear and increasing relation between stock return dispersions (as measured by CSAD) and market return does not hold during periods of large market movements in Africa.

The presence of investor herding means that market participants or investors ignore their private information and prior evaluation and follow the aggregate market view during periods of market stresses. As a result, the linear and increasing relationship between the variables disappears, giving way to a non-linear relationship where dispersions decrease or increase at a decreasing rate with higher market returns.

The findings in this study are consistent with prior studies. Niyitegeka and Tewari (2015) and Gilmour and Smit (2002), respectively, found evidence of herding in the Johannesburg stock exchange and Unit Trust Industry in South Africa. The evidence of herd behaviour in the present study further corroborates studies in other markets elsewhere (see for instance, Angela-Maria et al., 2015 for the CEE stock markets; Galariotis et al., 2015 for markets in the US and UK; Yao et al., 2014 for the Chinese stock markets; Balcilar et al., 2013 for GCC stock markets; and Bhaduri and Mahapatra, 2013 for Indian stock markets). However, the evidence of herd behaviour in this study is inconsistent with the evidence of no herding reported in El-Shiaty and Badawi (2014) and Demirer et al. (2007) concerning the Egyptian stock market.

In the second part of the analysis, the study examined whether the herding behaviour in Africa's emerging and frontier markets is influenced by the inception of the global financial crisis. A number of studies (Chiang and Zheng, 2010; Balcilar et al., 2013; Galariotis et al., 2015) have found evidence to the effect that financial crises affect the behaviour of investors stimulating them to herd. To confirm or reject this assertion, the CCK model

Table 2: Results of unit root tests

Stock market(Variable)	Test equation	ADF unit root test CSAD/Returns($R_{m,t}$)		PP unit root test CSAD/Returns ($R_{m,t}$)	
		Levels	1st difference	Levels	1st difference
Egypt (CSAD)	None	−1.988977**	−15.73623***	−15.47571***	−224.9222***
	Intercept only	−10.78126***	−15.72999***	−26.37700***	−224.8527***
	Intercept and trend	−11.41479***	−15.72563***	−26.19959***	−224.5467***
Egypt (Returns)	None	−32.46232***	−18.73603***	−32.59365***	−420.6553***
	Intercept only	−32.44919***	−18.72831***	−32.58102***	−420.3542***
	Intercept and trend	−32.49164***	−18.72055***	−32.59573***	−420.8042***
Kenya (CSAD)	None	−2.637397***	−24.70208***	−22.59987***	−604.4678***
	Intercept only	−24.17646***	−24.69457***	−36.99530***	−604.3518***
	Intercept and trend	−24.33710***	−24.68736***	−36.84118***	−605.6674***
Kenya (Returns)	None	−20.57062***	−18.94869***	−25.70467***	−322.9084***
	Intercept only	−20.56713***	−18.94343***	−25.69735***	−323.6983***
	Intercept and trend	−20.61983***	−18.93845***	−25.72865***	−323.3837***
Morocco (CSAD)	None	−0.335354	−20.23770***	−2.009283**	−580.9391***
	Intercept only	−23.35448***	−20.23109***	−36.82707***	−581.4089***
	Intercept and trend	−23.47334***	−20.22390***	−36.66750***	−580.5243***
Morocco (Returns)	None	−35.29195***	−17.97859***	−35.19078***	−368.0392***
	Intercept only	−35.30093***	−17.97276***	−35.20098***	−368.3611***
	Intercept and trend	−35.29021***	−17.96652***	−35.18931***	−367.9821***
Nigeria (CSAD)	None	−1.721536*	−17.39038***	−7.582778***	−188.3122***
	Intercept only	−10.14398***	−17.38473***	−26.06094***	−188.2277***
	Intercept and trend	−10.31894***	−17.37719***	−25.99525***	−187.9288***
Nigeria (Returns)	None	−25.83167***	−358.3743***	−25.86997***	−358.3743***
	Intercept only	−25.85017***	−358.2307***	−25.88945***	−358.2307***
	Intercept and trend	−25.89101***	−366.9693***	−25.89101***	−366.9693***
South Africa (CSAD)	None	−1.590337	−24.10713***	−12.41158***	−341.1161***
	Intercept only	−4.704401***	−24.10208***	−52.48266***	−341.0242***
	Intercept and trend	−5.096800***	−24.09693***	−53.36368***	−340.9637***
South Africa (Returns)	None	−47.62803***	−22.90325***	−47.85729***	−517.9314***
	Intercept only	−47.62077***	−22.89831***	−47.85147***	−517.7866***
	Intercept and trend	−47.61137***	−22.89369***	−47.84155***	−517.6404***

For each country, the unit root test results are reported for both CSAD and $R_{m,t}$, for three different test methods, and at level and first difference. ***, ** and *denote statistical significance at 1%, 5% and 10% levels, respectively

Table 3: Regression estimates of herd behaviour

Estimated equation: $CSAD_t = \gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t.$						
Market	Obs.	γ_0	γ_1	γ_2	R²	Adj. R²
Egypt	1233	0.0013*** (0.000)	0.533*** (0.000)	−0.050*** (0.000)	0.5079	0.5067
Kenya	1661	0.0008*** (0.000)	1.016*** (0.000)	−0.099*** (0.000)	0.6513	0.6507
Morocco	1458	0.0022*** (0.000)	3.703*** (0.000)	−1.177*** (0.000)	0.8571	0.8568
Nigeria	1661	0.0013*** (0.000)	1.528*** (0.000)	−0.192*** (0.000)	0.7127	0.7121
South Africa	2346	0.0004*** (0.000)	0.682*** (0.000)	−0.029*** (0.000)	0.8264	0.8262

The decision rule is that no herding occurs if $\gamma_1>0$ and $\gamma_2=0$, and herding is present if $\gamma_2<0$ and is statistically significant. The P-values are in parentheses with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

Table 4: Regression estimates of herd behaviour during global financial crisis

$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 D^{CRISIS} R_{m,t}^2 + \varepsilon_t$							
Market	Obs.	γ_0	γ_1	γ_2	γ_3^{CRISIS}	R²	Adj. R²
Egypt	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Kenya	1661	0.0009*** (0.000)	0.608*** (0.000)	−0.051*** (0.000)	0.904*** (0.000)	0.6952	0.6944
Morocco	1458	0.0025*** (0.000)	2.799*** (0.000)	−0.833*** (0.000)	2.079*** (0.000)	0.8883	0.8880
Nigeria	1661	0.0016*** (0.000)	0.974*** (0.000)	−0.131*** (0.000)	1.601*** (0.000)	0.7590	0.7584
South Africa	2346	0.0004*** (0.000)	0.466*** (0.000)	−0.013*** (0.000)	0.753*** (0.000)	0.8743	0.8741

The results in this table are based on the estimation of equation (3): $CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 D^{CRISIS} R_{m,t}^2 + \varepsilon_t$. The decision rule is that herding is present if $\gamma_3<0$, herding intensified during crisis if $\gamma_3<-1$, and herding did not intensify during crisis if $(0>\gamma_3>-1)$. The P-values are in parentheses, with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

(equation 3) was estimated and the results reported in Table 4. The results provide no evidence of herding behaviour, instead, anti-

herding behaviour overwhelmingly showed during the global financial crisis as positive and a statistically significant crisis-

herding coefficient $\gamma_3 D^{CRISIS}$ is perceived for all the markets. This implies that stock return dispersions (CSAD) and average market return are linearly related so that dispersion increases with increasing market return. The crisis effect of anti-herding behaviour in Africa's emerging markets is quite strong as the crisis-herding coefficients are either close to or greater than unity. Specifically, the crisis-herding coefficients for Morocco (2.079) and Nigeria (1.601) are both greater than unity, signifying that the subprime-global financial crisis did intensify anti-herding behaviour in these markets.

In comparison, a number of studies previously found herding behaviour to have declined or to have been entirely absent during crisis. For example, Hwang and Salmon (2004) observed herding behaviour to have declined during the Asian and Russian crisis periods. Tessaromatis and Thomas (2009) reported evidence of exaggeration of differences in the Athens stock exchange in some years as investors diverged from the market consensus. Garg and Gulati (2013) found equity return dispersions to have increased during periods of extreme price movements. It was noted that regulatory reforms and strong foreign investor presence in the Indian market may have led to improved rationality among market participants.

Also, the results in the current study are consistent with those by Philippas et al. (2013) who concluded that the global financial crisis did not intensify herding in the Real Estate Investment Trust (REIT) in the United States. However, the findings regarding the herding effects of financial crisis are inconsistent with evidence documented in studies including Balcilar et al. (2013), Klein (2013), Mobarek et al. (2014), Angela-Maria et al. (2015), and Galariotis et al. (2015). The conclusion in these studies, including Tan et al. (2008) and Economou et al. (2011), is that herding is more pronounced in periods of extreme market stress. A possible reason for the profound anti-herding behaviour in the present study is effective institutional reforms and continual efforts to achieve greater market integration with major global stock markets. These

reform efforts and the associated market integration and greater informational efficiency may have improved the sophistication of market participants in the Africa's emerging markets. For example, the World Economic Forum Competitiveness ranked the Johannesburg stock exchange (JSE) in South Africa as the number one regulated stock exchange worldwide for the two consecutive times in 2010 and 2011 (ASEA, 2014).

4.2. Asymmetric Effects of Different Market Conditions on Herding Behaviour

There is evidence supporting asymmetric herding behaviour under various market conditions (Chiang and Zheng, 2010; Economou et al., 2011). The market direction depicts periods when the market is rising or falling, when trading volume is high or low, and when volatility is high or low. The present study thus sought to analyse the asymmetric effects on herd behaviour in Africa's emerging and frontier markets in relation to these different market conditions. First, the CCK model specified as equations (4) and (5) are estimated to examine herding asymmetries during rising and declining markets, respectively. The results are presented in Table 5 (Panel A for rising market conditions and Panel B for declining market environments). The results in Panel A exhibit signs of asymmetric herding effects during a rising market as the asymmetric herding coefficient γ_2 is negative and statistically significant for all markets. In terms of herding asymmetry in declining markets, the results in Panel B point to the presence of asymmetric herding effects during bearish market conditions as negative and statistically significant asymmetric herding coefficients γ_2 are perceived for all markets. In consequence, the results Table 5 provide convincing evidence of asymmetric herding effects during rising and declining markets in Africa's emerging markets.

These results imply that stock return dispersions and average market returns are nonlinearly related during conditions of increasing and decreasing market returns. Thus the linearity assumption implicit in the CAPM is conflicted since an increase in

Table 5: Regression estimates in rising and falling market conditions

Panel A: Rising market environments (increasing market phases)						
Market	Obs.	γ_0	γ_1	γ_2	R^2	Adj. R^2
Egypt	610	2.058*** (0.000)	0.840*** (0.000)	−0.098*** (0.000)	0.5292	0.5268
Kenya	809	1.260*** (0.000)	1.082*** (0.000)	−0.097*** (0.000)	0.6073	0.6059
Morocco	724	3.493*** (0.000)	4.121*** (0.000)	−1.601*** (0.000)*	0.8540	0.8534
Nigeria	822	2.185*** (0.000)	1.879*** (0.000)	−0.278*** (0.000)	0.7426	0.7417
South Africa	1135	1.094*** (0.000)	0.612*** (0.000)	−0.030*** (0.000)	0.7875	0.7870
Panel B: Declining market environments (decreasing market phases)						
Market	Obs.	γ_0	γ_1	γ_2	R^2	Adj. R^2
Egypt	666	2.078*** (0.000)	0.621*** (0.000)	−0.045*** (0.015)	0.4594	0.4569
Kenya	851	1.279*** (0.000)	1.055*** (0.000)	−0.139*** (0.000)	0.7104	0.7094
Morocco	733	3.397*** (0.000)	3.566*** (0.000)	−0.949*** (0.000)	0.8690	0.8684
Nigeria	838	2.234*** (0.000)	1.312*** (0.000)	−0.156*** (0.000)	0.6863	0.6852
South Africa	1210	0.984*** (0.000)	0.753*** (0.000)	−0.031*** (0.000)	0.8663	0.8660

The results in this Table (Panel A) are based on the estimation of equation (4): $CSAD_t^{UP} = \gamma_0 + \gamma_1^{UP} \left| R_{m,t}^{UP} \right| + \gamma_2^{UP} \left(R_{m,t}^{UP} \right)^2 + \varepsilon_t$ while those in Panel B are based on the estimation of equation (5): $CSAD_t^{DOWN} = \gamma_0 + \gamma_1^{DOWN} \left| R_{m,t}^{DOWN} \right| + \gamma_2^{DOWN} \left(R_{m,t}^{DOWN} \right)^2 + \varepsilon_t$. The decision rule is that no asymmetric herding occurs if $\gamma_1 > 0$ and $\gamma_2 = 0$, and asymmetric herding is present if $\gamma_2 < 0$ and is statistically significant. The P-values are in parentheses, with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

the average market return, under such circumstances, causes stock return dispersions to decrease or increase but at a declining rate. Further inspection of the asymmetric herding coefficients however reveals that herding is more prevalent during a rising market in Morocco and Nigeria, and more prevalent during a declining market in Kenya, Morocco and Nigeria. Thus asymmetric effects on herd behaviour in relation to rising and declining market conditions are not homogenous in Africa as some markets show more prevalence in the up-markets and others in the down-markets. Market participants may herd during either of the market directions because such periods are associated with intense price movements and potentially high risks. Losing because all others have lost is perceived to be less harmful in many respects compared to gaining all alone in the stock markets.

In terms of cross-country comparison, the coefficients of the herding asymmetry in rising and falling markets for Morocco (−1.602 and −0.949, respectively) are the greatest in Africa followed by Nigeria with coefficients of −0.278 (for a rising market) and −0.156 (for a falling market). The South African market displays the least asymmetric herding coefficients (−0.030 and −0.031) for both rising and falling markets, respectively. This profound evidence of herding asymmetric regarding rising and falling markets is consistent with the findings in Chiang and Zheng (2010), who provided evidence of herding asymmetry in both rising and falling markets, with a relatively more profound asymmetric herding in the Asian markets during rising markets. Similarly, Economou et al. (2011) found evidence of significant herding asymmetries during different markets conditions.

As a robustness check on the findings of the asymmetric herding under different market returns, the present study estimated a modified version of the CCK model (specified as equation 6) in the spirit of Chiang and Zheng (2010) and the results are presented in Table 6.

The results in Table 6 confirm the presence of asymmetry of herding behaviour in Africa's emerging markets under different conditions of market returns. Specifically, the asymmetric herding coefficients γ_3 are negative and statistically significant for all markets. Similar to the previous findings based on the CCK model, the coefficients for Morocco (−1.204) and Nigeria (−0.179) suggest that herding asymmetry is more prevalent in the two markets compared to others. The South African market

exhibits the least prevalence of asymmetric herding effect under various market conditions.

Next, the asymmetric effects of herding behaviour in different market environments of high and low trading volumes are also investigated by estimating the CCK model specified as equations (7) and (8) respectively. The results are displayed in Table 7 (Panel A for days of high trading volumes and Panel B for days of low trading volumes). In Table 7, the asymmetric herding coefficients γ_2 are negative and statistically significant for all markets. It can be realised that herding asymmetry is relatively more prevalent during low trading volume periods than in days of high trading volumes in all the markets, except Morocco.

These results suggest that herding behaviour tends to be manifested more in periods of low trading volumes than in periods of high trading volumes in the African markets. The only exception is the results for the Moroccan stock market where the evidence rather supports the existence of relatively more pronounced asymmetric effect of high trading on herding behaviour.

A striking observation from the results in Tables 8 however is that the asymmetric herding coefficients are generally very low for both high volume days and low volume days and for all markets. A possible inference is that trading volume may not be a major influential factor in herding behaviour although it does contribute to investor herding. This could be for the simple reason that trading volumes are generally low in Africa's stock markets (except for South Africa) and may be regarded by investors as being less informative.

Placing the results in this study within the context of previous studies, Tan et al. (2008) provided analogous evidence of asymmetric herding in the B-shares of the Shanghai and Shenzhen markets during low trading periods. Tan et al. (2008) however reported evidence of investor herding in the high volume conditions for both A-share and B-share markets in Shanghai and Shenzhen markets. While this evidence contradicts the findings in this study, it is nonetheless similar to the evidence observed in the Moroccan stock market. Also, Economou et al. (2011) found robust evidence of herding asymmetry in relation to trading volume in the Spanish and Portuguese markets. Moreover, the findings in this study support Mobarek et al. (2014) who recently found significant herding effect during periods of low trading volumes in Ireland and Norway.

Table 6: Regression estimates in rising and falling markets based on modified chang, cheng and khorana model

The estimated model: $CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$						
Market	**Obs.**	γ_0	γ_1	γ_2	γ_3	**R²**	**Adj. R²**
Egypt	1233	1.529*** (0.000)	−0.041** (0.045)	0.533*** (0.000)	−0.051*** (0.000)	0.5088	0.5073
Kenya	1661	1.260*** (0.000)	0.046** (0.038)	1.048*** (0.000)	−0.109*** (0.000)	0.7104	0.7094
Morocco	1458	3.448*** (0.000)	−0.296*** (0.000)	3.739*** (0.000)	−1.204*** (0.000)	0.8618	0.8614
Nigeria	1661	2.220*** (0.000)	0.185*** (0.000)	1.497*** (0.000)	−0.179*** (0.000)	0.7173	0.7166
South Africa	2346	1.038*** (0.000)	−0.088*** (0.000)	0.685*** (0.000)	−0.031*** (0.000)	0.8364	0.8361

The results in this table are based on the estimation of equation (6): $CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t$. The decision rule is that no asymmetric herding effect occurs if $\gamma_1 > 0$ and $\gamma_2 = 0$, and asymmetric herding effect exists if $\gamma_2 < 0$ and is statistically significant. The P-values are in parentheses, with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

Table 7: Regression estimates of herd behaviour on days of high and low trading volumes

Panel A: Herd behaviour during days of high trading volumes						
Market	**Obs.**	γ_0	γ_1	γ_2	**R²**	**Adj. R²**
Egypt	290	1.770*** (0.000)	0.028*** (0.000)	−0.00014*** (0.000)	0.5169	0.5119
Kenya	310	1.433*** (0.000)	0.016*** (0.000)	−0.00005*** (0.000)	0.6382	0.6346
Morocco	370	3.426*** (0.000)	0.035*** (0.000)	−0.00012*** (0.000)	0.8628	0.8617
Nigeria	450	2.728*** (0.000)	0.025*** (0.000)	−0.00004*** (0.000)	0.6094	0.6068
South Africa	588	1.446*** (0.000)	0.058*** (0.000)	−0.00042*** (0.000)	0.6781	0.6764
Panel B: Herd behaviour during days of low trading volumes						
Market	**Obs.**	γ_0	γ_1	γ_2	**R²**	**Adj. R²**
Egypt	394	1.468*** (0.000)	0.045*** (0.000)	−0.00027*** (0.000)	0.5780	0.5747
Kenya	522	1.413*** (0.000)	0.019*** (0.000)	−0.00009*** (0.000)	0.7232	0.7216
Morocco	733	3.475*** (0.000)	0.0149*** (0.000)	−0.00001*** (0.000)	0.8113	0.8102
Nigeria	612	2.538*** (0.000)	0.024*** (0.000)	−0.00005*** (0.000)	0.6529	0.6512
South Africa	694	1.375*** (0.000)	0.037*** (0.000)	−0.00026*** (0.000)	0.6675	0.6661

The results in this table (Panel A) are based on the estimation of equation (7): $CSAD_t^{V-HIGH} = \gamma_0 + \gamma_1^{V-HIGH}\left|R_{m,t}^{V-HIGH}\right| + \gamma_2^{V-HIGH}\left(R_{m,t}^{V-HIGH}\right)^2 + \varepsilon_t$, while those

in Panel B are based on equation (8): $CSAD_t^{V-LOW} = \gamma_0 + \gamma_1^{V-LOW}\left|R_{m,t}^{V-LOW}\right| + \gamma_2^{V-LOW}\left(R_{m,t}^{V-LOW}\right)^2 + \varepsilon_t$. The decision rule is that no herding occurs if γ_1>0 and

γ_2=0, and herding is present if γ_2<0 and is statistically significant. The P-values are in parentheses, with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

Table 8: Regression estimates of herd behaviour on days of high and low volatility

Panel A: Herd behaviour during days of high volatility						
Market	**Obs.**	γ_0	γ_1	γ_2	**R²**	**Adj. R²**
Egypt	587	1.545*** (0.000)	0.321*** (0.000)	−0.006 (0.000)	0.4444	0.4416
Kenya	828	1.278*** (0.000)	0.980*** (0.000)	−0.092*** (0.000)	0.6331	0.6317
Morocco	715	3.502*** (0.000)	3.615*** (0.000)	−1.054*** (0.000)	0.8872	0.8867
Nigeria	450	2.729*** (0.000)	0.025*** (0.000)	−0.0006*** (0.000)	0.6094	0.6068
South Africa	1180	0.913*** (0.000)	0.688*** (0.000)	−0.028*** (0.000)	0.8735	0.8732
Panel B: Herd behaviour during days of low volatility						
Market	**Obs.**	γ_0	γ_1	γ_2	**R²**	**Adj. R²**
Egypt	660	1.472*** (0.000)	0.579*** (0.000)	−0.059*** (0.000)	0.4490	0.4465
Kenya	803	1.267*** (0.000)	1.414*** (0.000)	−0.175*** (0.000)	0.6859	0.6847
Morocco	713	3.415*** (0.000)	6.453*** (0.000)	−3.696*** (0.000)	0.8549	0.8543
Nigeria	818	2.538*** (0.000)	2.817*** (0.000)	−0.745*** (0.000)	0.6296	0.6282
South Africa	1136	1.106*** (0.000)	1.077*** (0.000)	−0.155*** (0.000)	0.7805	0.7799

The results in this table (Panel A) are based on the estimation of equation (9): $CSAD_t^{V-LOW} = \gamma_0 + \gamma_1^{V-LOW}\left|R_{m,t}^{V-LOW}\right| + \gamma_2^{V-LOW}\left(R_{m,t}^{V-LOW}\right)^2 + \varepsilon_t$, while those in Panel

B are based on the estimation of equation (10): $CSAD_t^{\sigma^2 LOW} = \gamma_0 + \gamma_1^{\sigma^2 LOW}\left|R_{m,t}^{\sigma^2 LOW}\right| + \gamma_2^{\sigma^2 LOW}\left(R_{m,t}^{\sigma^2 LOW}\right)^2 + \varepsilon_t$. The decision rule is that no herding occurs if γ_1>0

and γ_2=0, and herding is present if γ_2=0 and is statistically significant. The P-values are in parentheses, with ***, ** and * denoting statistical significance at the 1%, 5% and 10% levels of significance, respectively

In the final analysis, we examined the asymmetry of different market conditions relating to high and low periods of volatility. To this end, equations (9) and (10) are estimated and the results are reported in Table 8 (Panel A for days when volatility is high and Panel B for days when volatility is low). It can be perceived from the results in Table 8 that the coefficients for asymmetric effect of volatility are negative and statistically significant (except Egypt which coefficients are insignificant statistically). The results thus suggest evidence of asymmetric effect of volatility on herding behaviour.

In effect, differential herding behaviour is exhibited based on whether the market is in high volatility state or low volatility state. The Moroccan market seems to exhibit the greatest asymmetric effect of volatility herding in Africa with −1.054 and −3.696 asymmetric volatility coefficients for high and low volatility periods,

respectively. The evidence of asymmetric volatility herding in African markets corroborates the findings of some previous studies such as Lao and Singh (2011), Klein (2013) and Mobarek et al. (2014). Specifically, Lao and Singh (2011) found greater prevalence of herding asymmetry in the Chinese market relative to the Indian market. Mobarek et al. (2014) perceived significant asymmetric volatility herding coefficients in Denmark, Greece and Sweden during high and low volatility periods. There is however robust evidence of greater herding behaviour in Africa during low volatility days than in periods of high volatility. While this finding contradicts a number of studies (Tan et al., 2008; Klein, 2013; Mobarek et al., 2014) it may have implied a classic market sentiment. Conservative investing coupled with high risk aversion among investors in African markets may reverse herding tendencies during extremely high volatility periods. Thus the finding may be suggesting that investors become increasingly less confident about the investment

decisions of others in periods of extremely high volatility in the market. Since volatility is more or less a stylised fact about African markets, periods of high volatility may be associated with slowdown in investment activities, making the presence of minimum volatility a sufficient condition to trigger herd behaviour in these markets.

5. CONCLUSION

A general consensus of growing behavioural finance literature focusing on investor herding suggests the presence of herd behaviour in emerging equity markets owing to informational inefficiency and other factors unique to these markets. In this study, we explored investor behaviour by investigating their tendency to herd in Africa's emerging and frontier markets. The motives underlying investor herding, the theoretical underpinnings and the implications of such behaviour were highlighted in the introductory section. We subsequently reviewed the extant literature on herding and specified our herding measure in line with the CSAD measure proposed by CCK. Finally, the empirical results of the presence of herd behaviour and asymmetric effects on herding were reported and analysed.

On whole, evidence of herding behaviour was detected in Africa's emerging markets (South Africa, Egypt, Morocco, Kenya and Nigeria). The findings in this study suggest rejection of the assumption of linearity and increasing relationship between stock return dispersions and aggregate market return. Instead, the prediction of non-linear relationship between the two in the presence of herd behaviour during unusual market movements is upheld. Market participants tend to ignore their private signals and follow the market consensus during such periods. The intensity of herding is however nonhomogeneous across these markets as cross-country comparisons showed evidence of significant variations in the herding values. The South African market, for instance, is observed to exhibit the lowest level of herding compared to the other markets, suggesting the presence of relatively greater informational efficiency in that market.

The findings in this study further indicate convincing evidence of anti-herding behaviour during the 2007-2009 global financial crisis. Therefore, the linear and increasing relationship existed as stock return dispersions appeared to widen following an increase in average market return. Again, this finding is also heterogeneous among markets as some markets (Morocco and Nigeria) experienced greater anti-herding behaviour than others (South Africa, Egypt and Kenya). An implication of this finding is that most African markets remain relatively less integrated with the rest of the world, so that investors did not consider the global financial crisis as contagious.

An analysis of herding asymmetry under different market conditions additionally indicated the presence of asymmetric herding effects in Africa's emerging and frontier markets. The findings implied that herding behaviour differ depending on whether the market is rising or falling, whether trading volumes are high or low, and whether market volatility is high or low. Thus while herd behaviour can be said to exist in the emerging and frontier markets in Africa, some periods in time experience more herding activities than others. In effect, herding asymmetry is not homogenous. Specifically, the findings perceived that herding is more pronounced under conditions of rising markets, low trading volume, and low volatility periods for stock markets in Egypt, Morocco and Nigeria. Nevertheless, the stock markets in South Africa and Kenya showed asymmetric herding effects during declining markets, high trading volume and high volatility periods. Thus stock return dispersions during extreme downside movements, high trading volume and high market volatility are much higher in the South African and Kenyan markets compared to those in the stock markets in Egypt, Morocco and Nigeria.

The present study thus concludes that herding behaviour exists in Africa's emerging and frontier markets and that asymmetric herding effects are also present in these markets. However, the herding intensity and herding asymmetry are non-homogenous across markets, suggesting that herding is stronger in some markets than others and that it is more intense and pronounced in some market conditions than other conditions. Interestingly, the findings relating to crisis periods showed evidence of significant anti-herding behaviour (exaggeration of differences) as increase in aggregate market return led to increase in stock return dispersions in these markets.

The evidence of convergence of investor decisions or trading strategies in this study has far-reaching implications for the efficiency and development of stock markets. Investor herding can systematically cause mispricing in financial asset prices, market instability and asset bubbles. Herding can also be a major source of shock and volatility spillover in financial markets and can limit portfolio diversification advantages by increasing the transaction costs of asset portfolios. Therefore, we suggest that policymaking and regulating of financial markets in Africa need to consider the impact of herding activities and formulate policies to discourage or halt their existence. The range of policies could involve stepping up efforts to improve informational efficiency and flows in African financial markets, improve market regulation and encourage effective reportage of firms' information, promote greater market integration with advanced financial markets for technology transfers and market efficiency among others, and educate market participants on the need for rational decision making and discourage same from herding behaviour.

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