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Herding Behaviour in African Stock Markets: Evidence from South Africa, Nigeria, Egypt & Kenya

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Abstract

In the presence of herding, collective investor behaviour tends to gravitate toward the same or similar investments. When herding behaviour becomes widespread, it can create asset bubbles or market crashes through panic-driven buying and selling. Consequently, comprehending how markets might react during periods of crisis becomes crucial for effectively hedging against artificially inflated asset prices. The objective of this paper is to examine the herding behaviour of investors in African markets – namely South Africa, Nigeria, Egypt and Kenya – using weekly and monthly stock data from January 2000 to October 2023. The study applies the cross-sectional standard deviation of returns (CSSD) and the cross-sectional absolute deviation of returns (CSAD) to examine herding in both normal and turbulent times, particularly during periods of significant turbulence such as the Global Financial Crisis (GFC) in 2008/9 and the recent COVID-19 pandemic. The findings indicate the existence of herding behaviour in the four African stock markets across various periods, with herding being less prominent during highly turbulent phases like the GFC and the COVID-19 pandemic. Additionally, the study reveals a significant spillover from the South African stock market to Nigeria and Kenya during the GFC and to Egypt during the COVID-19 pandemic. Furthermore, U.S. investor sentiment, represented by the VIX index, does not appear to influence herding behaviour in African stock markets. This would suggest that the African markets are correlated and that there are instances of high indications of herding behaviour.

1.) Introduction and Background

Herding or 'herd behaviour' is a concept that explains how individual investor decisions are swayed by collective group actions. It refers to a process whereby economic agents tend to imitate the actions of others or make decisions based on the behaviour of their peers (Spyrou, 2013). This can lead to a collective and often irrational movement in markets, where individuals follow the crowd and suppress their own beliefs and knowledge. Within the realm of investments, herding behaviour emerges as a particularly captivating and relevant subject, as it directly intertwines with human nature. By impacting both individual decision-making and social interactions, herding behaviour has the potential to exert a profound influence on the global financial landscape (Spyrou, 2013).

In the presence of herding, collective investor behaviour tends to gravitate toward the same or similar investments. When herding behaviour becomes widespread, it can create asset bubbles or market crashes through panic-driven buying and selling (Johansen & Sornette, 1999; Dass, Massa & Patgiri, 2008). Consequently, comprehending how markets might react during periods of crisis becomes crucial for effectively hedging against artificially inflated asset prices. The ability to anticipate and navigate such situations can play a pivotal role in mitigating the risks associated with herd behaviour in financial markets. In addition, herding behaviour in financial markets can lead to either market inefficiency or to the inefficient reallocation of assets; this can be observed among individual investors and collective investors like mutual funds (Dass et al., 2008). The idea of 'clustering' in stock returns shares conceptual similarities with herding behaviour and forms the foundation for two methods used to identify herding: return dispersion (Christie & Huang, 1995) and nonlinear dispersion (Chang, Cheng & Khorana, 2000).

Therefore, an effective understanding of herding behaviour in financial markets is crucial as it sheds light on how market participants' actions can be influenced by social interactions and how such behaviour might impact asset prices and market dynamics. This valuable information not only benefits professional investors but also informs policymakers on appropriate action in the presence of herding. Policymakers and financial authorities recognise the destabilising impact of herding behaviour on markets and the heightened fragility it imparts to the financial system (IMF, 2000). Furthermore, detecting and characterising herding behaviour becomes an essential task, as herding diminishes market efficiency and complicates portfolio diversification efforts (Ferreruela & Mallor, 2020). Therefore, shedding light on the nature of herding behaviour is pivotal for devising measures to enhance market stability and optimise portfolio management strategies.

Numerous studies have delved into the phenomenon of herding behaviour, employing various methodological approaches to explore its implications in different contexts. However, a predominant focus of these studies lies within developed markets. For instance, Ukpong, Tan and Yarivaya (2021) delved into industry herding within the U.S. stock market, while Espinosa-Méndez and Arias (2021) and Ferreruela and Mallor (2020) directed their attention to European markets. More recently, China has also been a subject of exploration (Wu, Yang & Zhao, 2020; Li, Liu & Park, 2017). Additionally, some studies have undertaken an examination of the influence of fear and other factors on herding behaviour across various countries (Economou, Hassapis & Philippas, 2018; Aharon, 2020). Upon reflection, a noticeable gap exists in the literature concerning examinations of herding behaviour in the specific context of extreme market conditions within various African stock markets. The significance of this paper becomes apparent as the expansion and heightened appeal of African stock markets to foreign investors pivot on clarifying whether the market is perceived as 'safe' for investment.

Despite significant progress in understanding herding behaviour, past studies have faced certain limitations. Some methodological approaches might have struggled to capture the nuances of herding behaviour accurately, leading to potential inaccuracies in their findings. This could especially be true when taking different geographical locations into account. For instance, while many empirical studies utilise the measure proposed by Lakonishok, Shleifer and Vishny (1992; LSV hereafter) to provide insights into fund manager behaviour, it comes with notable drawbacks. The LSV measure can mistakenly identify herding when only a small number of investors are active, does not directly test for interdependence in institutional demand and fails to distinguish between managers following their own trades and those mimicking others. Additionally, it assumes short selling and relies on detailed fund holdings data, which is not always accessible (Wylie, 2005; Sias, 2004; Hwang & Salmon, 2004).

Furthermore, studies might have primarily focused on specific market segments or regions, limiting the breadth of their conclusions. For example, studies like those by Economou, Kostakis and Philippas (2011), Khan, Hassairi and Viviani (2012), and Mobarek, Mollah and Keasey (2014) all focused on developed European markets, potentially influenced by similar factors, thus limiting the generalizability of their results. In emerging markets, the issue is compounded by the lack of reliable and comprehensive data, which further hampers accurate analysis.

Comprehending herding behaviour's scope within and between African stock markets is essential for evaluating potential risks to investors' capital. This paper aims to analyse the presence of herding behaviour during two distinct shocks – the Global Financial Crisis (2008-2009) and the COVID-19 Pandemic (2020-2023). Given the inherent differences in their nature, with the Global Financial Crisis (GFC) being endogenous and the COVID-19 pandemic being exogenous (Ferreruela & Mallor, 2020), exploring how these shocks impact diverse African markets offers valuable insights.

This comparative analysis seeks to assist investors and policymakers in devising strategies to mitigate risks associated with both endogenous and exogenous shocks within the African context. The theoretical premise suggests that during periods of heightened volatility caused by shocks, exogenous and endogenous shocks in this case, herding behaviour is likely to occur as investors – intimidated by these shocks – tend to act more risk-averse (Spyrou, 2013). Consequently, this inclination towards herding behaviour may lead to a deficiency in independent due diligence and market research.

This paper focuses on the cross-sectional dispersion of stock returns and employs the pioneering measures by Christie and Huang (1995) and Chang, Cheng and Khorana (2000), who implemented the cross-sectional standard deviation (CSSD) and the cross-sectional absolute deviation (CSAD) models respectively. Using these measures, this study focuses on some of Africa's most significant stock markets – namely South Africa, Nigeria, Egypt and Kenya – and examines the extent to which herding behaviour may intensify during extreme market conditions, characterised by volatile fluctuations.

Building on this foundation, this paper extends its scope to delve into the intricate dynamics of herding behaviour between the South African stock market and the other aforementioned African stock markets. This analysis seeks to unravel the interconnectedness and spillover effect of herding behaviour within the South African context across other African countries. Lastly, this study extends its scope to examine the impact of U.S. investor sentiment, as proxied by the CBOE implied volatility index (VIX), on African stock markets. This broader perspective aims to provide a more nuanced understanding of how global factors may influence herding behaviour in the specific context of African stock markets.

In general, when investors are faced with extreme market conditions, they tend to suppress their own research or findings and conform to the overall market consensus. This study aims to examie herding behaviour with the goal of aiding governments in recognising and addressing its presence; this, in turn, can assist in the implementation of preventive measures to mitigate the formation of financial bubbles within these stock markets. Additionally, this study seeks to provide valuable insights to investors on how African stock markets tend to behave during volatile periods, thus enabling investors to better manage risk and diversify their portfolios more efficiently.

Given that these four nations collectively constitute approximately 45% of Africa's GDP (IMF, 2023) and exhibit a pronounced theoretical interconnectedness (Bello, Guo & Newaz, 2022), the study of herding behaviour gains significance due to the potential contagion effect during adverse and turbulent periods. This holds crucial implications for both policymakers and investors, directly influencing the safety of their investments and the resilience of regulated markets.

Moreover, the selection of these countries is based on the availability of readily accessible data in comparison to other African nations. Additionally, these four countries collectively cover the entire geographical spectrum of Africa, spanning North, East, South and West. Emphasizing the argument on interconnectedness, it is pivotal to recognize that the financial sector serves as a reliable barometer of overall economic well-being. Understanding its dynamics empowers governments to formulate effective strategies for fostering economic growth. In a highly connected market scenario, herding behaviour in one country could spill over to others, jeopardizing economic stability. Therefore, a comprehensive grasp of the extent and circumstances under which herding behaviour may manifest is imperative to collectively ensure the economic well-being of the African region.

Key stylised facts about herding behaviour in stock markets reveal that stock markets are generally more pronounced during periods of market stress, where uncertainty leads investors to follow collective trends, amplifying price swings (Wu, Yang & Zhao, 2020; Aharon, 2020). Herding behaviour is often viewed as a short-term phenomenon, showing stronger effects over shorter timeframes, particularly in less efficient markets like emerging or frontier markets where information dissemination is slower (Spyrou, 2013; Economou, 2016). Institutional investors are especially susceptible to herding, driven by pressures to conform and achieve short-term benchmarks, while certain sectors like technology and financials see more herding due to rapid changes and economic sensitivity (Lakonishok et al, 1992; Sias, 2004). Additionally, herding tends to be non-linear in nature, becoming more pronounced during extreme market movements and is often more visible in smaller, less liquid markets where independent information is limited (Christie & Huang, 1995; Chiang & Zheng, 2010). This behaviour contributes to market inefficiencies, including overreactions and eventual corrections as prices revert to more rational levels.

The paper proceeds as follows: Section 2 delves into the pertinent literature, Section 3 outlines the data, statistical properties and methodology employed and Section 4 analyses and discusses the results of the paper. Section 5 provides the conclusion and recommendations of the paper.

2.) Literature Review

As mentioned previously, herding behaviour in financial markets occurs when investors opt to emulate the trading practices of those they perceive as better informed or follow market consensus rather than acting based on their own information and convictions (Blasco, Corredor & Ferreruela, 2012a). Existing literature offers several reasons as to why investors herd.

Bikhchandani, Hirshleifer and Welch (1992), along with Banerjee (1992), presented a theoretical model elucidating how information transmission can result in imitation. Banerjee's (1992) sequential decision-making model emphasizes that each decision-maker considers the choices of preceding individuals, rationalised by the belief that these predecessors possess crucial information. Demonstrating that individual optimisation leads to decision rules fostering herding behaviour, Banerjee (1992) highlights the resulting inefficiencies in the equilibrium. Information asymmetry serves as a catalyst for imitation, as asymmetric or scarce information can escalate herding behaviour among investors (Baddeley, Curtis & Wood, 2004).

Moreover, concerns about reputation costs may drive herding behaviour, as managerial apprehensions about reputation and asymmetric information prompt imitation over innovation and risk-taking behaviour (Scharfstein & Stein, 1990; Chevalier & Ellison, 1999; Hong, Kubik

& Solomon, 2000). Maug and Naik (2011) contribute insights into the impact of fund managers' performance evaluation on asset allocation decisions. Their study reveals optimal contracts for delegated portfolio management consistently include relative performance elements. Maug and Naik (2011) further demonstrate that incorporating relative performance induces bias among fund managers leading towards deviation from return-maximizing portfolios in favour of benchmark alignment – which can be characterised as 'herding'.

Moreover, the examination of the impact of Black Swan events on investor behaviour has been a central theme in numerous studies across diverse market settings. These studies have consistently highlighted a robust relationship between herding behaviour and emotions, particularly as influenced by market sentiment (Corredor & Ferreruela, 2012b; Economou, Hassapis & Philippas, 2018; Hwang, Rubesam & Salmon, 2021). Notably, the occurrence of Black Swan events introduces an additional layer to this dynamic, amplifying the link between unexpected, extreme events and the tendency for investors to engage in herding behaviour, as evidenced in the cited research.

In times of heightened uncertainty, mutual imitation becomes more apparent as investors closely observe each other's actions and tend to mimic their peers' decisions (Kurz & Kurz-Kim, 2013; Schmitt & Westerhoff, 2017). During crises and pandemics, the cost and time required to process the vast amount of information generated escalates significantly, thereby increasing the incentives for herding behaviour. Research indicates that herding behaviour can amplify panic-driven decisions during such extreme market conditions (Brock, 1999). Certain market participants who are prone to imitating others exhibit heightened concern for short-term outcomes, contributing to panic situations. The phenomenon of 'fire sales' has been identified by researchers such as Pedersen (2009) and Brunnermeier (2009) as a risk to market stability and can amplify negative shocks.

Numerous studies have delved into the identification and estimation of herding behaviour. For example, Caparrelli, D'Arcangelis and Cassuto (2004) concentrated on the Italian stock market from 1988 to 2001, confirming the existence of herding, especially in extreme market conditions. Expanding their analysis to 18 markets spanning 1988–2009, Chiang and Zheng (2010) unveiled evidence of herding in both developed and Asian markets. They also pinpointed herding tendencies in the U.S. and Latin American markets during financial crises. In a study encompassing four European markets, Economou, Kostakis and Philippas (2011) observed herding effects primarily in the Greek and Italian markets. However, no such evidence surfaced for the Spanish market, and findings for Portugal remained inconclusive. The study underscored significant asymmetries in herding effects concerning rising and falling markets, as well as variations between days with high and low volatility, among other factors. A critique towards all these aforementioned studies is that they neglected developing markets – and especially neglected African markets – throughout their studies. Furthermore, these studies failed to look into the contagion effect between countries or regions.

The initial results of the study conducted by Christie and Huang (1995) – henceforth referred to as CH – conclude that there is a lack of consistency in daily and monthly U.S. data with regard to the existence of herd behaviour during episodes of substantial price fluctuations. Furthermore, the study conducted by Chang, Cheng and Khorana (2000) – henceforth referred to as CCK – investigated whether herding behaviour could be detected across five international markets, including the U.S., Hong Kong, Japan, South Korea and Taiwan. The research revealed a lack of conclusive evidence for herding behaviour in well-established markets such as the U.S. and Hong Kong, while indicating weaker signs of herding in Japan. In contrast, significant and robust evidence of herding behaviour was observed in emerging markets; namely, in the cases of South Korea and Taiwan. Again, a critique towards these studies is that they neglected developing countries and the possible spillover of herding behaviour from one country to another.

While the evidence of herding in both developed and emerging markets varies depending on the examined period and specific market conditions, there is a general anticipation that herding is more likely to be more pronounced in emerging markets. This expectation stems from the distinctive features associated with emerging markets, including thin trading, incomplete regulatory frameworks, limited transparency, information asymmetries and overall market inefficiencies (Kallinterakis & Kratunova, 2007). Frontier markets, being even less developed and less liquid than emerging markets, exhibit characteristics such as low trading volume, high concentration, limited access, inexperienced market participants and incomplete institutional frameworks (Economou, Gavriilidis, Kallinterakis & Yordanov, 2015).

Within the context of African stock markets, authors Aawaar, Boamah and Akotey (2020) utilised the CCK model and found evidence of investor herding in some of Africa's emerging and frontier markets. They concluded that Africa's primary markets remain relatively inefficient, presenting opportunities for investment strategies aimed at capitalising on market irregularities to generate excess returns. These countries include: South Africa, Egypt, Morocco, Kenya and Nigeria. Their study claims that the intensity of herding varies across different markets, with South Africa displaying relatively lower levels of herding relative to the other countries of interest.

In contrast to the study by Aawaar et al. (2020), which examined five countries, this paper will only focus on four of those countries. What distinguishes this paper from that of Aawaar et al. (2020) is that this paper will contribute towards existing literature by offering an updated perspective on herding behaviour in African stock markets by extending the timeframe from 2020 to 2023. This extended timeframe provides an opportunity to assess the lasting impacts of events like the COVID-19 pandemic and other global developments – such as the recent Russia-Ukraine conflict – on African markets.

Furthermore, in contrast to Aawaar et al. (2020), this paper aims to examine potential cross-country effects by acknowledging the potential correlations between African stock markets and the South African stock market – Africa's leading financial market. To address differences in trading schedules among these African countries, among other considerations, it was decided to utilise weekly prices. For instance, Egypt does not engage in trading on Mondays whereas the other countries do. This mismatch in trading days could give unreliable results, especially when studying cross-country effects. Opting for a weekly frequency solves this issue and enables a more thorough exploration of long-term correlations among these nations – see Section 3.3 for a more thorough explanation. Lastly, what distinguishes this paper from Aawaar et al. (2020) is its examination of the impact of U.S. investor sentiment on African stock markets. Aawaar et al. (2020) did not incorporate an international correlation component in their analysis, a criticism that this paper seeks to address.

The paper by Mertzanis and Allam (2018) utilised the models suggested by CH and CCK respectively in order to try and estimate herding behaviour within the Egyptian stock market. For the entire sample period, herding behaviour was not observed, but there is some evidence of non-linear adverse herding. Their study suggests that herding is not present in bull and bear markets. When analysing the pre- and post-Egyptian revolution (occurring during 2011) phases separately, there is weak evidence of adverse herding in both phases and adverse herding in bullish markets. However, the results do not provide conclusive evidence regarding bearish markets. A potential limitation of this study arises from its reliance on daily data, which, in theory, is preferred. However, it may suffer from subpar quality due to it being applied to African stock data. To address this data quality concern, this paper will attempt to rectify the situation by conducting its analysis on a weekly and monthly frequency instead of a daily frequency.

Recent studies have delved into the impact of investor sentiment on herding behaviour in stock markets, often employing the CBOE implied volatility index (VIX) as a proxy for U.S. investors' sentiment (Philippas, Economou, Babalos & Kostakis, 2013; Chiang, Lo & Nelling, 2013; Economou, Gavriilidis & Kallinterakis, 2015). The CBOE VIX, introduced in 1993, gauges expected future market volatility based on S&P500 options and serves as a barometer for investor sentiment, commonly referred to as the 'investor fear gauge' (Whaley, 2000; Whaley, 2009). Its international recognition stems from superior explanatory power compared to historical volatility (Siriopoulos & Fassas, 2009).

According to the affect infusion model (AIM, Forgas, 1995), positive mood reduces risk aversion, while negative mood increases it, influencing how individuals evaluate risky situations. In line with AIM, herding is expected to be more pronounced during increases in the VIX, reflecting pessimism and negative sentiment. Conversely, the mood maintenance hypothesis (MMH, Isen & Labroo, 2003; Isen & Patrick, 1983) suggests that people aim to maintain positive mood states, leading to increased caution in positive sentiment periods when the VIX decreases. Despite their opposing views, both theories agree that human behaviour varies during times of uncertainty (Aharon, 2020).

Economou, Hassapis and Philippas (2018) investigated herding behaviour in developed stock markets, emphasising the impact of investors' 'fear' on herding estimations. While their results show a statistically significant fear impact on herding, the study has limitations, being outdated and neglecting developing markets. Additionally, it lacks a focus on sub-samples, hindering the isolation of specific herding periods. Addressing these shortcomings is essential for a comprehensive understanding.

Aharon (2020) contributes a more recent study on uncertainty, fear and herding behaviour, exploring the relationship between market sentiment – captured by the VIX – and herding. The study covers 1990–2019 data for size-ranked portfolios, revealing a strong connection between the VIX and herding across various portfolio groups. Similar to Economou et al. (2018), it falls short by not addressing developing markets or examining sub-samples to identify specific herding periods.

3.) Data & Methodology

3.1.) Data

This study utilises weekly and monthly stock price data spanning from January 2000 to October 2023 for South Africa, Egypt and Kenya. However, data for Nigeria’s stock market is available only from February 2002, necessitating the commencement of Nigeria’s analysis from that date. When assessing the spillover effect from South Africa to Nigeria (Section 4.3), the data is specifically aligned starting from February 2002 to ensure an accurate comparison between the two markets over the same timeframe. Similar considerations for Nigeria apply to the examination of VIX implementation in Section 4.4.

The chosen period, January 2000 to October 2023, strategically encompasses significant global economic phases, including the GFC and the COVID-19 pandemic. This deliberate timeframe allows for an in-depth examination of how investor herd behaviour evolves across diverse market scenarios. The analysis covers the entire dataset as well as distinct sub-samples: pre-global financial crisis, global financial crisis, post-global financial crisis, COVID-19 pandemic and post-COVID-19 pandemic.

Following the recommendation by Kabir (2017) this study subcategorizes the periods for the 2008-2009 global financial crisis as follows: pre-crisis (1 January 2000 to 30 September 2008), global financial crisis (1 October 2008 to 1 April 2009), and post-crisis (2 April 2009 to 31 January 2020). The COVID-19 period starts on 1 February 2020, aligning with the World Health Organisation’s (WHO) declaration of the outbreak as a public health emergency of international concern (WHO, 2020). This phase extends until 31 January 2023, as per the WHO's announcement indicating stability in Africa's COVID-19 situation (WHO, 2023). Lastly, the post-COVID period was from 01 February 2023 until 03 October 2023.

Data for this study is sourced from Bloomberg. Specifically, the daily closing prices were downloaded for the Johannesburg Stock Exchange Top 40 index (JSE40) for South Africa, Nigerian Stock Exchange 30 Index (NGX30) for Nigeria, Egyptian Exchange 30 Index (EGX30) for Egypt and Nairobi Securities Exchange 25 Share Index (NSE25) for Kenya. These widely recognised indexes contain the largest and most liquid stocks of the respective countries and serve as proxies for each country's overall stock market. Major stock indexes are generally composed of large, well-established companies that collectively represent a substantial portion of total market capitalization. This composition provides a broad and reliable indicator of overall market trends. Additionally, these indexes prioritize highly liquid stocks to mitigate potential biases in estimations that can occur from thinly traded securities, an issue particularly relevant in emerging and frontier markets (Brooks et al., 2006), where trading volumes are often lower.

The selection of these indexes was informed by the imperative consideration of ensuring reliable, consistent and sufficiently long time-series data – a critical factor often constraining research focused on developing countries (Jerven, 2016; Kinyondo & Pelizzo, 2018). Overcoming the limitations imposed by data constraints is essential for conducting rigorous analytical work and enabling robust economic analysis. Thus, the chosen indexes for South Africa, Nigeria, Egypt and Kenya are characterized by their liquidity and data availability. To ensure data reliability, a thorough review of the data was conducted. This involved verifying completeness, excluding thinly traded companies, and addressing any instances of missing or incomplete return values to prevent breaks or inconsistencies. This approach helps ensure the analysis is built on a solid and reliable data foundation, facilitating more dependable conclusions in the study of herding behaviour. Descriptive statistics for weekly and monthly frequency data can be found in Section 4.1 and Appendix 1 respectively.

Additionally, the study incorporates the CBOE VIX for the U.S., also sourced from Bloomberg, with a daily frequency. The CBOE VIX gauges expected future market volatility based on S&P500 options and serves as a barometer for investor sentiment and anxiety (Whaley, 2009; Qadan & Aharon 2019) and for uncertainty and macroeconomic hazards (Bloom, 2009). The VIX is also commonly referred to as the 'investor fear gauge'. The rationale behind selecting the VIX, a U.S.-centric metric, to estimate fear and investor sentiment stems from the undeniable significance of the U.S. stock market is recognised as the largest, most prominent and influential stock market globally (World Federation of Exchanges, 2023). Consequently, the VIX emerges as a potent proxy for gauging the impact of fear or investor sentiment on herding behaviour in Africa.

Research indicates that herding behaviour tends to be more observable in daily data, particularly in emerging markets (Chang, Cheng & Khorana, 2000; Mertzanis & Allam, 2018). However, the limited availability of high-quality data posed a challenge. To address irregularities, low trading volumes, missing values, or other inconsistencies in certain stocks, this study transformed daily stock prices into weekly and monthly prices. Instead of significantly reducing the sample size by excluding these lower-quality data stocks that did not have consistent or reliable daily data, this paper chose to retain all stocks in their respective indices and utilise weekly and monthly prices instead, thereby enhancing data quality, reliability and consistency.

The inclusion of the monthly frequency broadens the scope of analysis by providing a benchmark for assessing market dynamics and sentiment, thus contributing to a comprehensive examination of investor herd behaviour across the selected African stock markets. An additional rationale for examining monthly stock prices is that asset managers frequently rebalance their portfolios on a monthly basis. Therefore, it is pertinent to analyse findings over this frequency, aligning with industry practices and contributing to a more comprehensive understanding of herding behaviour in the context of different timeframes.

This paper addresses missing data in two ways. Firstly, this paper changes the frequency of the data by transitioning from daily to weekly and monthly frequencies. This adjustment is crucial, especially for stocks in markets beyond the JSE, where accurate and consistent daily data is often lacking due to factors like low trading volumes, suboptimal data capturing, or limited resources. Secondly, this paper employs a methodology involving tracking all stocks constituting the index backwards. In other words, information for all stocks listed on the indices in October 2023 was retrieved as extensively as possible, acknowledging that certain stocks are incorporated into the dataset only after the dataset's initial commencement. While this introduces survivorship bias, obtaining a survivorship-free dataset in the context of African countries is challenging. The reliable and consistent historical constituents of indices are difficult to procure without substantial estimation efforts, adding complexity to data quality enhancement in this specific setting.

It is crucial to highlight that the primary emphasis of this paper's analysis will be on the weekly frequency, as theoretically, herding behaviour is expected to be more evident during this frequency relative to a monthly frequency. The inclusion of the monthly frequency is for completeness and comparison purposes. Therefore, the monthly results are only presented for the primary model of interest (i.e., the CCK / CSAD model); monthly outputs for the CH (CSSD) model and extensions of the CCK model are presented in the Appendix.

The weekly and monthly closing prices were transformed into continuously compounded returns (R_t) by taking the logarithmic difference of the price series. This implementation is represented by equation (1) below:

$$R_t = 100(\ln(p_t) - ln(p_{t-1})) \qquad \textbf{(1)}$$

3.2.) Model Specification

3.2.1.) Measuring Herding Behaviour

In this paper, the intensity of herding behaviour has been assessed through two general measures based on the dispersion of stock returns. To compute the return dispersion metric, this paper adopts the approach introduced by Christie and Huang (1995) and Chang, Cheng and Khorana (2000).

According to CH, we can use the cross-sectional standard deviation (CSSD) of returns for the stocks within a specific market to detect herding. In the presence of herding behaviour, the dispersion of returns would be lower than expected. The CSSD is estimated as follows:

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

where $R_{i,t}$ is the observed return of stock *i* at time *t* and $R_{m,t}$ is the equally-weighted average return of the *N* stocks listed on the market at time *t*.

In order to evaluate the degree to which return dispersion experiences a significant reduction during periods characterized by extreme market returns, thus indicating potential imitation among market participants, CH proposes the following regression model:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \epsilon_t \quad \textbf{(3)}$$

where $D^L{}_t$ represents a binary variable with a value of 1 when $R_{m,t}$ falls within the lower 5% of the returns distribution and 0 otherwise. Similarly, $D^U{}_t$ is a binary variable with a value of 1 when $R_{m,t}$ falls within the upper 5% of the returns distribution and 0 otherwise.

To assess the impact of the GFC and the COVID-19 Pandemic on herding behaviour, an alternative approach involves incorporating dummy variables for the respective time frames. This method mitigates the potential challenge of unevenly dividing the complete sample into sub-samples. Introducing dummy variables not only isolates the effects of the specified periods but also enhances the analytical depth. Thus, expanding equation (3) entails the addition of a dummy variable with a value of 1 during the designated periods of the GFC and the COVID-19 pandemic, and 0 otherwise. This adjustment is reflected in the following regression:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \beta^C D_t^C + \epsilon_t \quad \textbf{(4)}$$

Where the symbols represent the same variables as in equation (3), with the only addition being $D^C{}_t$ which represents a binary variable with a value of 1 for the periods of the GFC (1 October 2008 to 1 April 2009) and COVID-19 Pandemic (1 February 2020 – 31 January 2023) respectively and 0 otherwise. To independently isolate the effects of the two events, two separate regressions were conducted for the dummy variables associated with the GFC and the COVID-19 pandemic.

Within the framework of rational asset pricing models, when the coefficients of the dummy variables are negative and statistically significant, we fail to reject the null hypothesis and thus conclude that herding behaviour is present during extreme market conditions. Conversely, if the coefficients are positive and/or statistically insignificant, we reject the null hypothesis, leading to the conclusion that no herding behaviour is detected during these extreme market conditions. It is noteworthy to mention that the biggest critiques of the CH model are that it is sensitive to outliers, only takes linear relationships into account and that the model is often too strict in herding estimation.

The model proposed by CCK addresses some of the valid critiques of the CH model. This model is based on the cross-sectional absolute deviation (CSAD) of the returns which is drawn from the conditional version of Black's (1972) CAPM. The equation utilised is as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{n} |R_{i,t} - R_{m,t}| \tag{5}$$

The authors suggest that adherence to market consensus during pronounced price fluctuations may disrupt the conventional linear and positive correlation between market return and CSAD, potentially introducing non-linear or diminishing patterns. To accommodate these potential non-linearities in the relationship between dispersion and market return, they adopt a non-linear specification. This specification incorporates a parameter explicitly crafted to capture deviations from the anticipated linear trend, as depicted below:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \epsilon_t \tag{6}$$

In rational asset pricing models, the relationship is expected to be linear and positive. Specifically, the CSAD is expected to rise under extreme market conditions due to the diverse sensitivities of individual stocks to market returns. However, if herding behaviour is present then the relationship is expected to become non-linear, with the coefficient γ_2 subsequently becoming negative and statistically significant.

3.2.2.) Cross-Country Herding Effects

Herding behaviour warrants examination from regulatory and investment perspectives because interrelated markets can mutually influence each other, thus potentially magnifying imitative behaviour. This could in turn adversely impact market efficiency. Consequently, achieving geographical could become more challenging.

This phenomenon may be particularly relevant within Africa, where several smaller African stock markets might change their investment behaviour based on developments in the South African market – Africa's most developed and most liquid stock market (IMF, 2022). To investigate the connections between cross-sectional dispersions in these markets, this paper estimates the following model in order to try and capture the spillover effect from South Africa towards Nigeria, Egypt and Kenya:

$$CSAD_{i,t} = \alpha + \gamma_1|R_{m,i,t}| + \gamma_2 R^2_{m,i,t} + \gamma_3 R^2_{m\,JSE,t} + \gamma_4 CSAD_{JSE,t} + \epsilon_t \quad \textbf{(7)}$$

where, $R_{m,i,t}$ represents the equally-weighted average return of *N* stocks listed on market *i* at time *t* and $R_{m,JSE,t}$ denotes the equally-weighted average return of *N* stocks listed on the JSE at time *t*.

This study extends the benchmark model (equation 4) by incorporating additional explanatory variables; namely the squared equally-weighted average return of the JSE (γ_3) and the cross-sectional absolute dispersion of returns of the JSE (γ_4) in order to enhance the explanatory power of CSAD in the country. The presence of herding behaviour contagion from the JSE towards the i^{th} stock market is indicated by a positive and statistically significant $\gamma 4$ coefficient. Lastly, a $\gamma 3$ coefficient that is negative and significant indicates that herding formation in the i^{th} country is influenced by market conditions in South Africa.

3.2.3.) Investor Sentiment

Lastly, recognizing the substantial spill-over effects of U.S. investor sentiment on global stock markets (Bathia, Bredin & Nitzsche 2016), this paper investigates the impact of the VIX index, also known as the 'fear index', on the herding estimation in the respective African markets. Thus, this paper augments equation (4) by incorporating the rate of change in the fear index, resulting in the updated equation below:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \gamma_3 VIX_{k,t} + \epsilon_t \qquad \textbf{(8)}$$

where the variables are the same as in equation (6) above, where the $VIX_{k,t}$ is the return of the implied volatility of the U.S. Chicago Board Options Exchange's (CBOE) Volatility Index, a popular measure of the stock market's expectation of volatility based on S&P 500 index options.

In accordance with the findings by Economou, Hassapis and Philippas (2018), a negative and statistically significant γ3 coefficient suggests that investors' herding decisions are influenced by sentiment prevailing in the U.S. stock market. This aligns with the AIM theory discussed earlier, wherein a negative coefficient corresponds to increased herding during periods of negative sentiment. Conversely, a positive γ3 coefficient supports the MMH theory, also mentioned earlier.

4.) Results

Table 1: Descriptive Statistics (Weekly Frequency)

		Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	JB Test
South Africa	Rm	0.0008	0.0013	0.0565	-0.0957	0.0112	-0.6486	5.7681	1813***
	CSSD	0.0203	0.0186	0.1168	0.0057	0.0088	2.7170	16.9012	16331***
	CSAD	0.0132	0.0123	0.0516	0.0023	0.0051	1.7703	6.3681	2752***
		Mean	**Median**	**Max**	**Min**	**Std Dev**	**Skewness**	**Kurtosis**	**JB Test**
Nigeria	Rm	0.0009	0.0004	0.0631	-0.0718	0.0131	0.0010	3.8330	697***
	CSSD	0.0261	0.0234	0.2084	0.0000	0.0136	4.3473	43.7644	94173***
	CSAD	0.0166	0.0126	0.1465	0.0000	0.0152	2.8989	13.7851	10582***
		Mean	**Median**	**Max**	**Min**	**Std Dev**	**Skewness**	**Kurtosis**	**JB Test**
Egypt	Rm	0.0010	0.0013	0.0885	-0.1110	0.0162	-0.4378	5.8580	1820***
	CSSD	0.0269	0.0223	0.3738	0.0000	0.0241	7.7672	84.7603	384620***
	CSAD	0.0170	0.0114	0.2220	0.0000	0.0198	3.5570	21.1364	25768***
		Mean	**Median**	**Max**	**Min**	**Std Dev**	**Skewness**	**Kurtosis**	**JB Test**
Kenya	Rm	0.0004	0.0006	0.0597	-0.0381	0.0083	0.3488	4.1808	933***
	CSSD	0.0214	0.0182	0.1479	0.0051	0.0117	2.8544	16.2101	15304***
	CSAD	0.0135	0.0109	0.0763	0.0000	0.0100	2.0934	6.5933	3162***
VIX		**Mean**	**Median**	**Max**	**Min**	**Std Dev**	**Skewness**	**Kurtosis**	**JB Test**
		0.0003	-0.0076	0.9601	-0.4653	0.1284	0.8175	4.3895	1139***

Note: **: p = 0.1, **: p = 0.05, ***: p=0.01*

Table 1 above provides an overview of the weekly descriptive statistics for the return series, CSSD and CSAD series in the aforementioned African stocks and return of the VIX index. As is expected with stock market data, the R_m, CSSD and CSAD values exhibit a positive mean for all four markets. South Africa has the lowest values for both CSSD and CSAD, whereas Egypt has the highest values for both CSSD and CSAD. Volatility, as measured by the standard deviation, seems to be relatively high for most variables in all markets, with South Africa having the lowest standard deviation among all the countries across all variables.

The descriptive statistics indicate that most variables display both skewness and heavy-tailed properties, with each series showing evidence of a leptokurtic distribution due to all variables displaying excess kurtosis (i.e. kurtosis > 3). In particular, R_m, CSSD and CSAD are all positively skewed, with the exception of South Africa's and Egypt's R_m. Positive skewness suggests an asymmetric tail extending towards higher values, while negative skewness indicates an asymmetric tail extending towards lower values in the distribution. Thus, the skewness values indicate that most of the R_m, CSSD and CSAD values are greater than their respective means.

Regarding the VIX variable, its mean of 0.0003 suggests an average percentage change very close to zero, indicating minimal directional trend on average. The negative median implies a skew towards smaller negative changes, indicating more instances of moderate downward movements than upward movements. The VIX variable exhibits higher volatility relative to other variables, evident in its elevated StdDev. A positive skewness of 0.8175 suggests a right-skewed distribution, implying a longer tail of positive changes. A kurtosis value of 4.3895 indicates leptokurtosis, signifying fatter tails than a normal distribution and a higher probability of extreme positive or negative changes.

Lastly, the Jarque-Bera normality test statistics strongly indicate the presence of non-normal behaviour in these series, thus reinforcing the excess kurtosis and skewness measures. Regarding the descriptive statistics for monthly frequency, it can be found in Appendix 1.

4.1.) Herding Behaviour Estimated by CSSD

The CH model (equation 3) was estimated as the first part of the analysis, with the results displayed in Table 2 below.

Table 2: Estimation of Herding Behaviour using CSSD – Christie and Huang (1995)

Panel A: South Africa	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.019*** (0.0002)	0.020*** (0.0003)	0.025*** (0.003)	0.017*** (0.0002)	0.023*** (0.003)	0.018*** (0.001)
DLt5%	0.019*** (0.001)	0.014*** (0.001)	0.021*** (0.005)	0.014*** (0.001)	0.030*** (0.003)	0.009 (0.005)
DUt5%	0.016*** (0.001)	0.011*** (0.011)	0.016*** (0.005)	0.017*** (0.001)	0.023*** (0.001)	0.020 (0.009)

Panel B: Nigeria	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.023*** (0.0003)	0.024*** (0.001)	0.035*** (0.004)	0.023*** (0.003)	0.021*** (0.001)	0.025*** (0.002)
DLt5%	0.025*** (0.001)	0.035*** (0.004)	0.023*** (0.007)	0.019*** (0.001)	0.023*** (0.004)	0.014 (0.007)
DUt5%	0.029*** (0.001)	0.036*** (0.003)	0.023*** (0.009)	0.027*** (0.002)	0.024*** (0.004)	0.017*** (0.002)

Panel C: Egypt	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.023*** (0.001)	0.026*** (0.001)	0.027*** (0.004)	0.020*** (0.004)	0.022*** (0.002)	0.025*** (0.002)
DLt5%	0.035*** (0.003)	0.031*** (0.005)	0.053*** (0.008)	0.037*** (0.003)	0.030*** (0.008)	0.019 (0.005)
DUt5%	0.051*** (0.003)	0.063*** (0.005)	0.037*** (0.011)	0.042*** (0.004)	0.043*** (0.007)	0.030*** (0.009)

Panel D: Kenya	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	Covid-19	Post-COVID-19
α	0.019*** (0.0003)	0.026*** (0.001)	0.034*** (0.005)	0.018*** (0.0004)	0.022*** (0.002)	0.018*** (0.001)
DLt5%	0.019*** (0.001)	0.019*** (0.002)	0.001 (0.006)	0.020*** (0.002)	0.030*** (0.008)	0.021*** (0.005)
DUt5%	0.025*** (0.001)	0.026*** (0.002)	0.033*** (0.012)	0.016*** (0.002)	0.043*** (0.007)	0.023 (0.009)

Note: **: p = 0.1, **: p = 0.05, ***: p=0.01.Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023*

The presence of herding is contingent upon the beta coefficients being both negative and statistically significant. In examining the aforementioned stock exchanges across different periods – namely the complete sample, pre-crisis, crisis, post-crisis, COVID-19 and post-COVID-19 – it is evident that herding behaviour is not detected throughout the study period and across the countries. This conclusion is drawn from the observation that the beta values for all stock exchanges either exhibit positive values or lack statistical significance. To gauge the influence of the GFC and the COVID-19 pandemic on herding behaviour, the alternative approach – as illustrated in equation (4) – involves incorporating dummy variables for the corresponding time frames, thereby isolating the effects of these specified periods. The implementation of this alternative estimation does not alter the conclusions drawn from the CH model, as no herding behaviour is detected in any of the complete samples or sub-samples.

It is important not to be disheartened by the absence of herding behaviour detected using this measure. Prior studies, such as Blasco and Ferreruela (2008) and Chen (2013) have demonstrated instances where this measure proves overly restrictive, failing to identify herding in markets where alternative measures have succeeded. This limitation is anticipated, given that the CSSD exclusively estimates linear relationships. Another contributing factor may also stem from the weekly frequency possibly eroding the detection of short-term herding behaviour. Even though this outcome was expected, the CH model was included in this paper for completeness. It is noteworthy to mention that this measure is designed to detect herding primarily during extreme moments. This prerequisite implies that if imitation occurs at other times, this model may not capture it.

4.2.) Herding Behaviour Estimated by CSAD

In the second part of this study, the CCK model was implemented (equation 6). The results are displayed in Table 3 below.

Table 3: Estimation of Herding Behaviour using CSAD – Chang, Cheng and Khorana (2000) – Weekly Frequency

Panel A: South Africa	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.011*** (0.0002)	0.013*** (0.0005)	0.016*** (0.003)	0.010*** (0.0003)	0.012*** (0.001)	0.012*** (0.001)
γ1 ($\|R_m\|$)	0.188*** (0.03)	0.210** (0.082)	0.248 (0.267)	0.112 (0.073)	0.268*** (0.067)	-0.305*** (0.414)
γ2 (R^2)	2.925*** (0.647)	-2.180 (2.954)	1.158 (4.951)	4.441 (3.025)	1.736* (0.976)	25.129 (23.262)

Panel B: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.013*** (0.001)	0.010*** (0.001)	0.033*** (0.01)	0.012*** (0.001)	0.012*** (0.001)	0.011*** (0.002)
γ1 ($\|R_m\|$)	0.227*** (0.1)	0.877*** (0.082)	-0.526 (0.75)	0.520*** (0.145)	0.268*** (0.067)	-0.147 (0.287)
γ2 (R^2)	10.460*** (2.251)	-15.786*** (4.190)	30.961*** (10.151)	0.305 (3.612)	1.736* (0.976)	23.979*** (8.129)

Panel C: Egypt	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.008 (0.007)	0.011*** (0.001)	0.011 (0.01)	0.010*** (0.001)	0.014*** (0.002)	0.008 (0.007)
γ1 ($\|R_m\|$)	0.427 (0.1)	0.688*** (0.143)	0.112 (0.611)	0.167 (0.146)	-0.348*** (0.264)	0.427 (0.982)
γ2 (R^2)	14.798 (2.251)	-4.101*** (2.318)	17.454*** (5.956)	18.503*** (3.215)	26.149*** (4.934)	14.798 (23.624)

Panel D: Kenya	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,009*** (0.001)	0.009*** (0.001)	0.011 (0.010)	0.010*** (0.001)	0.009*** (0.001)	0.009*** (0.002)
γ1 ($\|R_m\|$)	0.0875*** (0.089)	0.812*** (0.145)	1.781 (1.040)	-0.261 (0.162)	0.300 (0.264)	0.247 (0.691)
γ2 (R^2)	-7.065** (3.002)	-15.011*** (4.328)	-18.894 (5.956)	59.806*** (8.653)	58.501*** (4.934)	75.371 (46.847)

Note: **: p = 0.1, **: p = 0.05, ***: p=0.01.Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-*2023

These results, as captured by Table 3 above, indicate slight evidence of herding behaviour in Africa's emerging and frontier markets. Herding behaviour, as captured by a negative and statistically significant value of $\gamma 2$, can be found in all markets–- excluding South Africa–- for the pre-crisis period (i.e. 2000-2007; before Basel III was implemented). The value of $\gamma 2$ for South Africa is in fact also negative for this period, but the value is highly insignificant. Thereafter, no significant herding behaviour was detected in South Africa by the model. Additionally, there was no herding behaviour detected for the complete sample, with the exception of Kenya. An explanation for herding behaviour being detected in Kenya's stock market for the entire sample period could indicate that the country has the least efficient and least developed stock market among the countries studied as, theoretically, less efficient stock markets will exhibit more herding behaviour.

The lack of herding behaviour in all markets after the GFC, as deduced from the positive and statistically insignificant values of $\gamma 2$, could be indicative that African markets became more efficient over time and that the regulatory changes implemented after GFC conceivably made markets more efficient and transparent. South Africa's lack of significant herding behaviour across all time frames may be indicative of the country's higher level of market transparency, liquidity and efficiency. Additionally, the lack of herding behaviour post-GFC suggests that market participants may have become more cautious and independent post-crisis. Market participants could have become more suspicious of others' actions, leading to reduced imitation as a potential risk mitigation strategy in anticipation of future crises. This behaviour, a characteristic of risk-averse individuals, implies that market participants were less inclined to follow market consensus after the GFC compared to before it.

These findings align with the findings of Aawaar et al. (2020), who observed the absence of herding behaviour in South Africa. Moreover, consistent with the observations made by Aawaar et al. (2020), this study reveals a consistent identification of herding behaviour in the emerging markets of Africa.

Table 4: Estimation of Herding Behaviour using CSSD – Chang, Cheng and Khorana (2000) – Monthly Frequency

Panel A: South Africa	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.025*** (0.001)	0.026*** (0.002)	0.052*** (0.008)	0.023*** (0.002)	0.028*** (0.002)	0.076*** (0.014)
$\gamma 1$ ($\lvert R_m \rvert$)	-0.086 (0.072)	-0.074 (0.206)	-2.282* (0.846)	-0.066 (0.239)	-0.168 (0.143)	-5.726** (1.818)
$\gamma 2$ (R^2)	5.758*** (0.987)	-2.180 (2.954)	49.794* (16.949)	6.921 (6.125)	6.203*** (1.332)	145.338** (50.788)

Panel B: Nigeria	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.032*** (0.004)	0.017*** (0.005)	0.025 (0.020)	0.022*** (0.004)	0.037*** (0.010)	0.033* (0.015)
$\gamma 1$ ($\lvert R_m \rvert$)	-0.271 (0.180)	1.153*** (0.422)	1.654* (0.537)	0.996*** (0.257)	-1.298* (0.657)	-0.595 (1.343)
$\gamma 2$ (R^2)	8.768*** (1.452)	-19.826*** (6.580)	1.157 (2.546)	-9.718*** (2.530)	24.103*** (7.478)	0.685 (19.889)

Panel C: Egypt	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.030*** (0.004)	0.023*** (0.007)	0.064 (0.061)	0.013** (0.005)	0.041*** (0.010)	0.045 (0.025)
$\gamma 1$ ($\lvert R_m \rvert$)	-0.133 (0.202)	0.986** (0.406)	-0.770 (1.942)	1.100*** (0.308)	-1.192** (0.479)	-1.223 (2.336)
$\gamma 2$ (R^2)	8.114*** (1.818)	-9.620** (4.485)	14.300 (10.697)	-6.695*** (3.376)	20.657*** (3.976)	8.284 (40.067)

Panel D: Kenya	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.030*** (0.001)	0.030*** (0.003)	0.048** (0.011)	0.031*** (0.002)	0.035*** (0.006)	0.031 (0.016)
$\gamma 1$ ($\lvert R_m \rvert$)	0.626*** (0.106)	0.803*** (0.190)	0.135 (0.563)	0.354** (0.167)	-0.089 (0.618)	-0.735 (5.153)
$\gamma 2$ (R^2)	4.219*** (1.367)	3.398 (2.446)	5.738 (4.724)	7.172** (3.216)	14.085 (10.083)	26.160 (332.043)

Note: **: p = 0.1, **: p = 0.05, ***: p=0.01.Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023*

As anticipated, there is no apparent evidence of herding behaviour in South Africa over any time frame on a monthly basis. However, it appears that herding behaviour is present in Nigeria and Egypt during non-turbulent times (i.e. Pre-Crisis and Post-Crisis), but it diminishes during times of crisis (i.e. the GFC & COVID-19). Consequently, it is anticipated that herding behaviour is likely to resume in Nigeria and Egypt in the aftermath of the COVID-19 crisis as markets become less volatile and return to historical levels.

Contrary to expectations, Kenya exhibits no discernible herding behaviour at any point when considering monthly frequency – similar to South Africa. This observation is intriguing as Kenya's stock market is relatively less developed compared to the other examined countries, which would traditionally suggest a higher likelihood of herding behaviour being detected. However, this is not evident in the data. The absence of herding behaviour in Kenya may suggest it is potentially a stable investment destination in the long term, particularly for those concerned about the impact of herding behaviour; the same can be said for South Africa. Nevertheless, it is crucial to recognize that numerous factors contribute to determining a country's suitability for investment. This observation is an additional consideration within the broader investment hypothesis in deciding investment suitability for a particular country.

The absence of negative and statistically significant $\gamma 2$ coefficients during the crisis period across all markets indicates a lack of herding behaviour. This observation may signify that, in times of crisis, investors in these markets become wary of the actions taken by their peers, thus leading to reduced imitation. Essentially, participants may opt for individual investment decisions based on their own information – or selectively imitate specific investors – rather than conforming to the broader market consensus. This phenomenon is found for both weekly and monthly frequencies.

The finding that herding behaviour is more pronounced over a monthly frequency compared to a weekly frequency challenges the conventional view that herding is primarily a short-term phenomenon, more evident over shorter timeframes. Typically, herding is expected to manifest over brief periods due to the quick reaction of investors to market events (Spyrou, 2013). However, one possible explanation for the stronger herding behaviour over a monthly horizon could be that investors have more time to digest economic data, corporate earnings reports and broader macroeconomic developments. As more time passes, information becomes more aggregated and consistent, allowing the dominant market narrative or trend to become clearer.

This suggests that herding may not always be a short-lived phenomenon, but could take time to fully develop and influence market behaviour, as noted by Christie and Huang (1995). With a longer time horizon, investors are more likely to converge towards a consensus view as market signals solidify – especially in the case of prolonged trends, such as sustained bull or bear markets. This collective interpretation of available information may cause stocks to move more closely together, reducing the dispersion in returns (as measured by CSAD) and making herding behaviour more noticeable. In contrast, over shorter periods, such as weeks, investors may react differently to fragmented and shorter-term pieces of information, leading to a broader range of trading decisions. Consequently, the dispersion in stock returns tends to be higher during these shorter periods, reflecting diverse investor responses.

This pattern may be particularly relevant in the context of emerging and frontier markets, where the flow and processing of information tend to be slower and less efficient compared to developed markets (Spyrou, 2013; Economou, 2016). In these markets, it may take longer for economic and financial information to be fully absorbed by market participants, thereby contributing to more pronounced herding behaviour over longer timeframes. This finding contrasts with previous studies, such as those by Aawaar et al. (2020) and Christie and Huang (1995), who argue that herding is typically a short-term phenomenon best captured with high-frequency data like daily observations.

Therefore, the results of this study may provide new insights into how Africa's emerging and frontier markets differ from developed markets in terms of herding behaviour over time. The slower dissemination and absorption of information in these markets could explain why herding is more pronounced over longer periods. Nonetheless, further research and peer review are necessary to validate these findings and fully understand the implications of herding behaviour in different market environments.

4.3.) Cross-Country Herding Behaviour Estimated by CSAD

To examine the relationship of cross-sectional dispersions between South Africa and the other relevant African countries, equation (7) was implemented. The results are displayed in Table 5 below.

Table 5: Estimation of Cross-Country Herding Behaviour – Weekly Frequency

Panel A: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,009*** (0.001)	0,008*** (0.002)	0,033** (0.014)	0,01*** (0.002)	0,003 (0.00003)	0,011 (0.009)
γ1 ($\lvert R_{m,t}\rvert$)	0,227** (0.098)	0,88*** (0.176)	-0,612 (0.899)	0,502*** (0.144)	-0,161 (0.267)	0,714 (0.821)
γ2 ($R^2_{m,t}$)	9,514*** (2.227)	-15,839*** (4.202)	32,285** (12.377)	0,389 (3.605)	18,029** (7.636)	-21,737 (25.954)
γ3 ($R^2_{JSE,t}$)	4,592*** (1.27)	-0,735 (3.900)	-1,645 (7.265)	8,746** (4.080)	2,136 (1.344)	23,573 (25.608)
γ4 ($CSAD_{JSE,t}$)	0,223** (0.091)	0,133 (0.16)	0,095 (0.716)	0,124 (0.140)	0,531*** (0.17)	-0,284 (0.692)

Panel B: Egypt	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,006*** (0.001)	0,005* (0.003)	-0,017 (0.018)	0,009*** (0.002)	0,008* (0.004)	0,004 (0.015)
γ1 ($\lvert R_{m,t}\rvert$)	0,301*** (0.083)	0,678*** (0.141)	0,421 (0.486)	0,167 (0.146)	-0,184 (0.273)	0,472 (1.016)
γ2 ($R^2_{m,t}$)	9,864*** (1.334)	-4,095* (2.280)	14,725** (4.881)	18,457*** (3.222)	19,815*** (5.675)	14,238 (24.35)
γ3 ($R^2_{JSE,t}$)	3,221** (1.509)	12,629*** (4.174)	**-30,014***** (7.330)	4,241 (4.573)	2,674 (2.31)	-18,939 (36.891)
γ4 ($CSAD_{JSE,t}$)	0,336*** (0.100)	0,356* (0.16)	1,900** (0.809)	0,002 (0.158)	0,347 (0.24)	0,423 (1.001)

Panel C: Kenya	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0,005*** (0.001)	0,007*** (0.002)	0,001 (0.015)	0,009*** (0.001)	0,005*** (0.002)	0,009** (0.004)
γ1 ($\|R_{m,t}\|$)	0,876*** (0.087)	0,824*** (0.145)	2,25* (1.147)	-0,292* (0.161)	0,470* (0.241)	-0,042 (0.691)
γ2 ($R^2_{m,t}$)	-8,972*** (2.947)	-15,290*** (4.328)	-32,793 (25.675)	61,026*** (8.596)	41,089*** (12.093)	88,464* (46.468)
γ3 ($R^2_{JSE,t}$)	2,596*** (0.809)	-1,863 (2.707)	7,259 (6.818)	3,841* (2.195)	0,653 (0.727)	**-21,179*** (11.227)
γ4 ($CSAD_{JSE,t}$)	0,275*** (0.055)	0,203* (0.104)	0,177 (0.778)	0,180** (0.075)	0,281*** (0.087)	0,199 (0.298)

Note: **: p = 0.1, **: p = 0.05, ***: p=0.01.Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023*

The results from Table 4 display a strongly positive and statistically significant relationship between the CSADs of South Africa and the other countries of interest; namely, Nigeria, Egypt and Kenya. More specifically, the relationships seem to be statistically significant for the entire sample period and various subsequent subsamples after the GFC. In other words, investor behaviour within the JSE had a statistically significant impact on herding behaviour within the relevant countries.

The relationship between South Africa, Nigeria and Kenya is significant over the entire sample, with the relationships getting stronger during the COVID-19 period in both cases. Contrastingly, the relationship between CSADs of South Africa and Egypt is positive and highly statistically significant for the entire sample and significant at the 10% and 5% level of significance for the pre-crisis and crisis sub-samples respectively. This contrasting observation can potentially be categorized based on geographical distinctions. The geographical context suggests the existence of a distinctive relationship among Sub-Saharan African countries. This dynamic appears absent in the case of Egypt – which could potentially serve as a representative proxy for North African countries. Further study is required to ascertain whether a distinct relationship exists between North African countries and Sub-Saharan countries.

A statistically significant negative coefficient observed in R^2_{JSE} suggests that herding behaviour within the specified African country is influenced by prevailing market conditions in South Africa. The coefficients indicate that during the GFC period, Egypt's herding formation was notably affected by market conditions in South Africa. In contrast, during the post-COVID-19 period, Kenya's herding formation exhibited a discernible correlation with market conditions in South Africa.

This finding shows that international diversification on the African continent may be difficult to achieve, as positive and significant $\gamma 4$ coefficients indicate correlated risk in the respective markets and the South African stock market. However, it seems that different markets are correlated during different times. Thus, a dynamic asset allocator could achieve improved diversification should they strategically allocate between the African markets given where we are in the business cycle.

In examining monthly data, the results for Egypt closely align with those obtained at a weekly frequency. The $CSAD_{JSE}$ remains statistically significant for all intervals leading up to the GFC but diminishes for all periods post-GFC. In the case of Nigeria, the $CSAD_{JSE}$ demonstrates statistical significance for the 2009-2020 timeframe, accompanied by a negative and statistically significant R-squared, indicating the presence of herding behaviour during this period. Interestingly, this significance is not sustained during the 2020-2023 period. Conversely, Kenya exhibits a negative and statistically significant $CSAD_{JSE}$ for the entire sample period. However, this significance does not extend to any specific sub-periods.

The identified statistical significance of spillover effects in Egypt during the GFC, coupled with the absence of such effects during the COVID-19 pandemic, implies a potential correlation between Egypt and South Africa stemming from endogenous shocks. Consequently, if an endogenous shock materializes, prudent investors may consider divesting from either the Egyptian or South African stock market, particularly if concerns arise about the potential contagion of herding behaviour between these markets. Conversely, Nigeria and Kenya exhibit notable spillover effects from the South African stock market during the COVID-19 sub-sample, with no such effects during the GFC. This suggests a plausible relationship between Nigeria, Kenya and South Africa influenced by exogenous shocks. Therefore, in the event of an exogenous shock and apprehensions about spillover effects from the South African market, diversifying out of that market could be a wise strategy. However, it is essential to note that additional research is necessary to substantiate these hypotheses.

4.5.) Investor Fear and Herding Behaviour Estimated by CSAD

To examine the relationship of U.S. investor sentiment on the relevant African countries, equation (8) was implemented. The results are displayed in Table 6 below.

Table 6: Estimation of Investor Fear and Herding Behaviour – Weekly Frequency

Panel A: South Africa	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.011*** (0.001)	0.013*** (0.001)	0.018*** (0.004)	0.01*** (0.001)	0.012*** (0.001)	0.012*** (0.001)
γ1 ($\|R_{m,t}\|$)	0.189*** (0.030)	0.209* (0.082)	0.076 (0.330)	0.115 (0.073)	0.263*** (0.068)	-0.320 (0.424)
γ2 ($R^2_{m,t}$)	2.894*** (0.649)	-2.151 (2.963)	4.125 (5.970)	4.362 (3.025)	1.856 (1.000)	26.105 (23.887)
γ3 (VIX_t)	0.001 (0.001)	-0.000 (0.002)	0.008 (0.009)	0.001 (0.001)	-0.002 (0.003)	0.002 (0.006)

Panel B: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.013*** (0.001)	0.010*** (0.001)	0.033** (0.011)	0.012*** (0.001)	0.011*** (0.002)	0.010* (0.005)
γ1 ($\|R_{m,t}\|$)	0.221* (0.100)	0.871*** (0.176)	-0.438 (0.824)	0.519*** (0.144)	-0.156 (0.286)	0.606 (0.786)
γ2 ($R^2_{m,t}$)	10.610*** (2.255)	-15.726*** (-0.005)	29.383* (11.723)	0.135 (3.594)	24.072*** (8.080)	-18.739 (24.892)
γ3 (VIX_t)	0.004 (0.003)	-0.005 (0.006)	-0.008 (0.027)	0.010** (0.004)	0.011* (0.006)	-0.019 (0.021)

Panel C: Egypt	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.011*** (0.001)	0.011*** (0.001)	0.010 (0.011)	0.010*** (0.001)	0.014*** (0.002)	0.009 (0.007)
γ1 ($\|R_{m,t}\|$)	0.321*** (0.084)	0.690*** (0.143)	0.250 (0.682)	0.173 (0.144)	-0.288 (0.269)	0.286 (0.926)
γ2 ($R^2_{m,t}$)	10.335*** (1.323)	-4.134* (2.316)	15.856* (6.886)	18.307*** (3.173)	25.020*** (5.029)	19.251 (22.312)
γ3 (VIX_t)	0.015*** (0.003)	0.009 (0.007)	0.019 (0.040)	0.015*** (0.004)	0.009 (0.008)	0.062* (0.027)

Panel D: Kenya	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.009*** (0.000)	0.009*** (0.001)	0.009 (0.010)	0.011 (0.001)	0.009*** (0.001)	0.009 (0.002)
γ1 ($\|R_{m,t}\|$)	0.873*** (0.089)	0.821*** (0.145)	1.953 (1.094)	-0.267 (0.161)	0.282 (0.250)	0.259 (0.705)
γ2 ($R^2_{m,t}$)	-7.181* (2.992)	-15.163*** (4.329)	-20.629* (24.458)	59.865 (8.612)	56.21*** (12.079)	74.909 (47.625)
γ3 (VIX_t)	0.006** (0.002)	0.005 (0.004)	-0.015 (0.025)	0.005 (0.002)	0.006* (0.003)	0.002 (0.010)

Note: *: p = 0.1, **: p = 0.05, ***: p=0.01.Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023

Table 6 above delves into the impact of 'fear' on herding estimation. Despite some evidence of herding towards market returns (observed in Nigeria, Egypt and Kenya in the pre-crisis period, as well as Kenya in the crisis period, consistent with Section 4.2 findings), there is no clear evidence of herding towards the 'fear' indicator. None of the countries exhibits a negative and statistically significant γ3 coefficient (indicating that an increase in implied volatility indices is negatively related to CSAD). Thus, the VIX does not play a significant and consistent role in triggering herding behaviour for all countries in this study at a weekly frequency, with each regression showing either a positive or statistically insignificant relationship.

The results for the monthly frequency are analogous to the weekly frequency. South Africa, Nigeria and Egypt show no distinct evidence of herding towards the 'fear' indicator. In other words, the VIX does not significantly trigger herding behaviour in these countries. However, Kenya stands as an exception, displaying statistically significant herding towards the U.S. ‘fear’ indicator for the complete sample and the pre-crisis sub-sample (i.e. from 2000-2008) for a monthly frequency. This is evidenced by the negative and statistically significant value of the γ3 coefficient (see Appendix 5).

The reasons for this are not entirely clear, but a potential hypothesis is that regulatory improvements in the Kenyan stock market, initiated in 2006 – including demutualization, enhanced regulation and the introduction of automated trading systems – may have altered investors’ relationship with uncertainty and ‘fear’ (Nairobi Stock Exchange, 2023). These changes allowed for remote trading, thus potentially reducing the impact of fear and uncertainty on investment decisions, positioning Kenya as a safer and more reliable investment opportunity (Nairobi Stock Exchange, 2023).

Considering that asset managers tend to invest and rebalance on a monthly frequency, the fact that investors no longer physically had to be on the trading floor to invest in Kenya could mean that investors did more due diligence and research to invest in Kenya instead of basing their investment decisions in Kenya on investors' fear and sentiment. However, this is a hypothesis that requires further investigation to precisely understand its implications within Kenya and only within Kenya for a monthly frequency, but not for a weekly frequency.

These findings contrast other studies conducted in a developed market context (Economou, Hassapis & Philippas, 2018; Aharon, 2020). This divergence may be attributed to African markets being potentially distant from the 'global' proxy that the VIX theoretically encapsulates. Furthermore, including other fear proxies, such as the South African Volatility Index (SAVI), in future studies could yield different results.

5.) Conclusion and Recommendations

This paper examines herding behaviour in four of Africa's developing and frontier markets – South Africa, Nigeria, Egypt, and Kenya – focusing on periods of high volatility, specifically the 2008–2009 Global Financial Crisis and the 2020–2023 COVID-19 pandemic. This paper also explores whether common herding forces operate across these markets, particularly investigating potential spillover effects from the South African stock market to those in Nigeria, Egypt and Kenya. Additionally, the paper assesses the influence of U.S. investor sentiment, represented by the VIX index (or "fear" index), on herding behaviour in African stock markets. The findings reveal evidence of herding behaviour within these African markets and suggest spillover effects across them, though little evidence was found that the VIX significantly influences herding in African markets.

Herding behaviour was not detected using the cross-sectional standard deviation (CSSD) model as suggested by Christie and Huang (1995). This was expected as this is a very stringent method of estimating herding behaviour (Spyrou, 2013). Furthermore, the results of this paper show that when implementing the cross-sectional absolute deviation (CSAD), first estimated by Chang, Cheng and Khorana (2000), does in fact find evidence of herding behaviour during various market sub-samples and within various markets. South Africa did not display any statistically detectable herding behaviour over any of the sample periods over any frequency.

This was somewhat expected, as South Africa is considered to have the most efficient stock market in Africa (Heymans & Santana, 2018).

More interestingly, Nigeria, Egypt and Kenya all indicate statistically significant indications of herding behaviour during the pre-crisis period (i.e. 2000-2007) and none thereafter for a weekly frequency. This could be the indication that African markets all became more efficient after the GFC in 2008. Reasons for this might be due to either the rules and regulations placed after the GFC (i.e. Basel III) ensured more efficient markets, or investors learned from their previous mistakes and focussed on making independent decisions instead of simply following the market trends.

Intriguingly, herding behaviour was found to be more prevalent for the monthly frequency relative to the weekly frequency, going against a stylised fact of herding behaviour. Even though South Africa did not display any herding behaviour for this frequency either, all other markets displayed indications of herding behaviour. Both Egypt and Nigeria displayed evidence of herding behaviour during the pre-crisis and post-crisis sub-periods. However, Kenya did not display any signs of herding behaviour of this frequency. This is relatively unexpected, as theory suggests more inefficient markets to display more profound levels of herding behaviour. The slower dissemination and absorption of information in less efficient markets might explain why herding is more pronounced over longer periods. However, Kenya's lack of herding suggests other factors may be at play. These findings challenge conventional expectations, highlighting the need for further research and peer review to better understand herding behaviour in emerging and frontier markets

Furthermore, this study did find evidence of cross-country herding behaviour across South Africa towards Nigeria, Egypt and Kenya. There was a strongly positive significant relationship between CSADs of countries for the complete period and varying sub-samples. Occurrences in the South African market, as captured by a statistically significant squared-return coefficient, display an increasingly positive relationship as time goes on for a weekly frequency.

Finally, this study incorporated the VIX index as a proxy for U.S. investor sentiment. The results for both weekly and monthly frequencies indicate that U.S. investor sentiment generally does not exert a profound effect on herding behaviour within African stock markets. An exception is observed in the Kenyan stock market for the complete sample and the pre-crisis period (2000-2008) for a monthly frequency.

The macrocycle reveals a noteworthy correlation between South Africa and Sub-Saharan Africa, as well as South Africa and Egypt in North Africa. Exploring avenues for diversification within these cycles is imperative. In periods of recession caused by endogenous shocks, strategic investments diversifying away from either South Africa or Egypt could be advantageous, given two this relationship's susceptibility to endogenous shocks. Should endogenous shocks become apparent and herding behaviour is deemed as alarming in an investor's portfolio, it would be wise to diversify away from one of the two countries. Additionally, if an investor is worried about potential herding when considering either Nigeria or Kenya for investments, it would be wise to consider excluding South Africa from their investments should an exogenous shock become apparent.

It raises intriguing questions about the potential influence of geographical location on these dynamics. The connection between Egypt and South Africa seems rooted in market and financial connections, whereas the physical and geographical connection between Kenya, Nigeria and South Africa warrants further investigation. These insights provide a foundation for more nuanced and region-specific investment strategies.

For investors considering the allocation of capital within African countries as a means of diversification, adopting a dynamic asset allocation process is likely to mitigate exposure to herding behaviour within each individual African stock market examined in this study. However, it is essential to note that all markets under consideration in this study exhibited signs of contagion from the JSE (South Africa's stock market). This should be taken into account when making investment decisions in Africa. Furthermore, it is observed that the VIX does not consistently act as significant a trigger for herding behaviour in African countries. This observation implies that U.S. investor sentiment or 'fear' is unlikely to exert a significant influence on herding behaviour in Africa. Consequently, African investments could serve as a valuable diversification option for investors seeking to diversify away from U.S. equities.

Policymakers should know that African markets are correlated and the markets contain, in some instances, high indications of herding behaviour. It should be noted that herding behaviour within individual African countries decreased over time in all markets. However, the spillover effect of herding behaviour between markets is still prevalent. This could adversely affect market stability and make bad times even worse due to the contagion effect. It is suggested that policymakers should aim to implement rules that will differentiate their financial systems from each other. African markets should pay specific attention to their relationship with the South African stock market and implement rules and regulations that will make them less dependent on the South African market. Lastly, the findings of this paper indicate that policymakers need not overly concern themselves with U.S. investor sentiment triggering herding behaviour within African stock markets.

In conclusion, while herding behaviour poses a notable factor in the dynamics of African stock markets, it is a manageable phenomenon that warrants careful consideration from both investors and policymakers. The insights gained from this study emphasise the need for a nuanced approach to decision-making. Investors looking to navigate the complexities of African markets should incorporate these findings into their strategic planning, utilising diversification opportunities and recognizing the influence of the South African stock market. Similarly, policymakers should acknowledge the correlated nature of African markets and work towards implementing rules that foster independence, mitigating the potential adverse effects of herding behaviour. By integrating these research findings into their decision-making processes, investors and policymakers can contribute to enhancing the overall quality and informed nature of financial decisions, ultimately fostering greater stability and resilience within African financial systems.

5.1.) Suggestions For Further Study

Expanding the analysis to include all African stock markets could yield a more comprehensive understanding of regional herding patterns, capturing the unique dynamics of each market and offering valuable insights for regulators and investors. While data limitations currently restrict such an analysis, future improvements in data availability and quality across African markets could enable broader studies that encompass countries this research could not include. This expanded scope would deepen insights into herding behaviour across diverse African economies and contribute to more targeted regulatory and investment strategies.

Additionally, the countries within this study vary widely in historical development. Thus, it would be interesting to look at countries that have had similar development and have a similar market structure (i.e. Maghreb Region (Morocco, Algeria, Tunisia, Libya and Mauritania), West Africa (Nigeria, Ghana, Senegal, Ivory Coast, Mali), East Africa (Kenya, Tanzania, Uganda, Rwanda and Burundi) or Southern Africa (South Africa, Zimbabwe, Zambia, Namibia and Botswana). Lastly, it would be interesting to see the extent to which different market structures (i.e. Western Africa versus Southern Africa) contribute to herding behaviour.

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Appendix

Appendix 1. Descriptive Statistics (Monthly Frequency)

		Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	JB Test
South Africa	R_m	0,003507	0,005918	0,07185	-0,11578	0,021599	-0,58637	2,687749	105***
	CSSD	0,040713	0,037413	0,179382	0,017798	0,016203	2,947324	18,82909	4680***
	CSAD	0,026481	0,024727	0,089109	0,011263	0,009433	1,976472	7,607198	885***

		Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	JB Test
Nigeria	R_m	0,003487	0,00293	0,135794	-0,18579	0,032115	-0,45368	5,476972	334***
	CSSD	0,053362	0,047251	0,228649	0	0,026142	2,102754	9,156792	1096***
	CSAD	0,034464	0,025388	0,371575	-3,8E-18	0,037068	3,951169	27,91523	9061***

		Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	JB Test
Egypt	R_m	0,004065	0,005464	0,130488	-0,16548	0,035767	-0,30369	2,354205	72***
	CSSD	0,058437	0,051809	0,373443	0	0,035857	4,024059	26,11612	8973***
	CSAD	0,036558	0,023207	0,330961	-5,2E-18	0,040534	2,711423	12,64181	2276***

		Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis	JB Test
Kenya	R_m	0,001951	0,003029	0,099629	-0,10131	0,024975	-0,16102	2,750025	93***
	CSSD	0,043544	0,039348	0,127761	0,013845	0,020499	1,646691	3,339031	265***
	CSAD	0,043544	0,039348	0,127761	0,013845	0,020499	1,646691	3,339031	265***

Appendix 2. Estimation of Herding Behaviour using CSSD – Christie & Huang (1995) – Monthly Frequency

Panel A: South Africa	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.038*** 0.001	0.038*** (0.001)	0.051*** (0.007)	0.036*** (0.001)	0.040*** (0.004)	0.020*** (0.001)
DLt5%	0.0.034*** (0.004)	0.027*** (0.005)	0.025 (0.012)	0.022*** (0.007)	0.048*** (0.011)	0.011 (0.004)
Dut5%	0.027*** (0.004)	0.022*** (0.004)	0.020*** (0.004)	0.021** (0.008)	0.043*** (0.013)	0.023 (0.01)

Panel B: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.049*** (0.003)	0.112*** (0.024)	0.049*** (0.001)	0.066*** (0.007)	0.050*** (0.020)	0.054*** (0.007)
DLt5%	0.028*** (0.001)	0.038*** (0.004)	0.032*** (0.007)	0.041*** (0.001)	0.025*** (0.009)	0.019 (0.021)
Dut5%	0.053*** (0.012)	0.036*** (0.003)	0.066*** (0.007)	0.049*** (0.002)	0.050** (0.020)	0.022 (0.020)

Panel C: Egypt	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.052*** (0.002)	0.060*** (0.004)	0.062* (0.024)	0.045*** (0.002)	0.049*** (0.002)	0.032*** (0.009)
DLt5%	0.048 *** (0.008)	0.029*** (0.017)	0.079 (0.038)	0.039*** (0.007)	0.107*** (0.013)	0.023 (0.007)
Dut5%	0.090*** (0.008)	0.112*** (0.014)	0.034 (0.048)	0.065*** (0.010)	0.037*** (0.009)	0.037*** (0.010)

Panel D: Kenya	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.039*** (0.001)	0.042*** (0.002)	0.056** (0.016)	0.038*** (0.001)	0.036*** (0.003)	0.028*** (0.003)
DLt5%	0.037*** (0.004)	0.033*** (0.010)	0.042 (0.023)	0.029*** (0.005)	0.037*** (0.013)	0.029*** (0.005)
Dut5%	0.055*** (0.004)	0.054*** (0.005)	0.038*** (0.014)	0.041*** (0.008)	0.051*** (0.008)	0.027 (0.015)

Note: *: p = 0.1, **: p = 0.05, ***: p=0.01
Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023

Appendix 3. Estimation of Herding Behaviour using CSSD – Christie & Huang (1995) – Dummy Variable (Monthly Frequency)

Panel A: GFC Dummy	α	DLt5%	DUt5%	D1Rmt	D2Rmt
South Africa	0.038*** 0.001	0.038*** (0.001)	0.051*** (0.007)	0.036*** (0.001)	0.040*** (0.004)
Nigeria	0.0.034*** (0.004)	0.027*** (0.005)	0.025 (0.012)	0.022*** (0.007)	0.048*** (0.011)
Egypt	0.027*** (0.004)	0.022*** (0.004)	0.020*** (0.004)	0.021** (0.008)	0.043*** (0.013)
Kenya	0.038*** 0.001	0.038*** (0.001)	0.051*** (0.007)	0.036*** (0.001)	0.040*** (0.004)

Panel B: COVID-19 Dummy	α	DLt5%	DUt5%	D1Rmt	D2Rmt
South Africa	0.038*** 0.001	0.038*** (0.001)	0.051*** (0.007)	0.036*** (0.001)	0.040*** (0.004)
Nigeria	0.0.034*** (0.004)	0.027*** (0.005)	0.025 (0.012)	0.022*** (0.007)	0.048*** (0.011)
Egypt	0.027*** (0.004)	0.022*** (0.004)	0.020*** (0.004)	0.021** (0.008)	0.043*** (0.013)
Kenya	0.038*** 0.001	0.038*** (0.001)	0.051*** (0.007)	0.036*** (0.001)	0.040*** (0.004)

Note: *: p = 0.1, **: p = 0.05, ***: p=0.01
Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023

Appendix 4. Estimation of Cross-Country Herding Behaviour – Monthly Frequency

Panel A: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,013** (0.006)	0,011 (0.01)	-0.014 (0.042)	0.001 (0.007)	0,052** (0.021)	0,006 (0.036)
γ1 (Abs.Rm)	-0.374** (0.176)	1,144** (0.432)	2.789 (1.136)	0,935*** (0.252)	-0.704 (0.587)	-1.784 (2.105)
γ2 (Rm Squared)	8,681*** (1.405)	**--19.701***** (6.712)	-4.492 (5.538)	-10.181*** (6.318)	7.269 (7.877)	13.985 (28.495)
γ3 (Rm Squared JSE	2,803 (2.235)	-0,389 (4.295)	-25.512 (20.859)	8.462 (6.318)	15.088*** (4.551)	26.683 (37.447)
γ4 (CSAD JSE)	**0,750***** (0.243)	0,133 (0.16)	0.707 (0.900)	**0.831***** (0.277)	-0.882 (0.687)	1.244 (1.453)

Panel B: Egypt	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,006 (0.008)	-0,001 (0.012)	-0,757* (0.079)	0,008 (0.010)	0,026 (0.027)	0.063 (0.047)
γ1 (Abs.Rm)	-0,047 (0.200)	0,823** (0.410)	-22,734* (0.486)	1,116*** (0.307)	-1.136** (0.541)	-2.388 (3.223)
γ2 (Rm Squared)	6,455*** (1.881)	**-7,593*** (4,568)	54,972* (4.881)	-6,971** (3.222)	20.891*** (7.126)	26.402 (57.080)
γ3 (Rm Squared JSE	0,635 (2.629)	-3.157 (5.543)	**797,235***** (79,252)	-13,367* (7.638)	-3.297 (8.046)	-30.303 (36.123)
γ4 (CSAD JSE)	**0,890***** (0.256)	**0,992***** (0.405)	**31,027*** (2,976)	0,338 (0.347)	0,537 (0.863)	0.146 (1.390)

Panel C: Kenya	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0,032*** (0.002)	0,034*** (0.004)	0,051** (0.002)	0.032*** (0.003)	0,038*** (0.008)	0,054 (0.033)
γ1 (Abs.Rm)	0,636*** (0.106)	0,828*** (0.193)	0.096 (0.098)	0.356** (0.169)	0,624 (0.939)	-0.741 (5.314)
γ2 (Rm Squared)	**4.049*** (1.367)	2.801 (2.476)	3.601 (0.821)	7.171** (3.257)	8.925 (7.423)	28.099 (344.587)
γ3 (Rm Squared JSE	**2,544*** (1.494)	7.621 (6.660)	31.842* (4.123)	1.676* (7.306)	8.925 (7.423)	107.582 (95.783)
γ4 (CSAD JSE)	**-0.213**** (0.107)	-0.483 (0.314)	-0.817 (0.193)	-0.069 (0.285)	-0.635 (0.519)	-3.481 (3.450)

Note: *: p = 0.1, **: p = 0.05, ***: p=0.01
Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023

Appendix 5. Estimation of Investor Fear and Herding Behaviour – Monthly Frequency

Panel A: South Africa	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.025*** (0.001)	0.026*** (0.002)	0.051* (0.005)	0.024*** (0.002)	0.029*** (0.002)	0.071** (0.016)
γ1 (Abs)	-0.086 (0.072)	-0.072 (0.208)	-1.568 (0.637)	-0.085 (0.240)	-0.189 (0.142)	-5.206* (1.965)
γ2 (R^2)	5.758*** (0.99)	4.241 (4.399)	30.509 (14.013)	7.846 (6.202)	6.409*** (1.326)	133.684* (53.958)
γ3 (VIX)	-0.000 (0.002)	-0.001 (0.005)	0.028 (0.012)	0.003 (0.003)	-0.005 (0.004)	-0.011 (0.013)

Panel B: Nigeria	**Complete Sample**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**COVID-19**	**Post-COVID-19**
α	0.032*** (0.004)	0.016** (0.005)	0.018 (0.029)	0.022*** (0.004)	0.038*** (0.011)	0.026 (0.014)
γ1 (Abs)	-0.282 (0.180)	1.342** (0.434)	1.823 (0.780)	0.992*** (0.259)	-1.320* (0.668)	0.308 (1.390)
γ2 (R^2)	8.815*** (1.451)	-23.146** (6.821)	0.515 (3.469)	-9.668*** (2.554)	24.012*** (7.578)	-15.188 (21.489)
γ3 (VIX)	0.011 (0.009)	-0.026 (0.016)	-0.018 (0.049)	0.002 (0.011)	0.007 (0.017)	-0.052 (0.037)

Panel C: Egypt	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.030*** (0.004)	0.023** (0.007)	0.097 (0.073)	0.014** (0.005)	0.038*** (0.010)	0.045 (0.028)
γ1 (Abs)	-0.113 (0.199)	0.988* (0.408)	-1.216 (2.076)	0.989** (0.304)	-1.010* (0.486)	-1.219 (2.588)
γ2 (R^2)	7.632*** (1.797)	-9.818* (4.512)	12.826 (11.215)	-5.312 (3.331)	19.025*** (4.057)	7.172 (44.581)
γ3 (VIX)	0.035*** (0.010)	0.012 (0.021)	0.199 (0.224)	0.038** (0.013)	0.025 (0.017)	-0.013 (0.047)

Panel D: Kenya	Complete Sample	Pre-Crisis	Crisis	Post-Crisis	COVID-19	Post-COVID-19
α	0.030*** (0.001)	0.029*** (0.002)	0.052* (0.016)	0.031*** (0.002)	0.035*** (0.006)	0.031 (0.018)
γ1 (Abs)	0.627*** (0.105)	0.830*** (0.185)	0.012 (0.731)	0.353* (0.167)	-0.113 (0.626)	-0.698 (5.743)
γ2 (R^2)	4.343** (1.363)	3.352 (2.367)	6.319 (5.753)	7.172* (3.227)	14.987 (10.315)	19.816 (371.491)
γ3 (VIX)	-0.006* (0.003)	-0.019** (0.007)	0.012 (0.030)	-0.001 (0.004)	-0.006 (0.010)	-0.004 (0.023)

Note: *: p = 0.1, **: p = 0.05, ***: p=0.01
Complete Sample: 2000-2023; Pre-crisis: 2000-2008; Crisis: 2008-2009; Post Crisis: 2009 – 2019; COVID-19:2019-2022; Post COVID-19:2023-2023