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-RESEARCH ARTICLE-

TESTING THE INFLUENCE OF HERDING BEHAVIOR ON THE JOHANNESBURG SECURITIES EXCHANGE (JSE) BEFORE, DURING AND AFTER THE FINANCIAL CRISIS

Raramai Patience Munetsi

University of the Western Cape,
Bellville, Cape Town, South Africa.
E-mail: patiencemunetsi@gmail.com
https://orcid.org/0000-0002-4132-0735

Pradeep Brijlal

University of Cape Town.
Rondebosch, Cape Town, South Africa.
E-mail: pradeep.brijlal@uct.ac.za
https://orcid.org/0000-0003-4437-9545

─Abstract─

This study assesses the presence of herding behavior in the context of the Johannesburg Stock Exchange (JSE) tradable sector in South Africa. The study employs four indices, namely Financials (FINI15), Industrials (INDI25) and Resources (RESI10), and the JSE All Share Index for the period from January 2007 to December 2017, using the FTSE/JSE All Share Index as a benchmark. Statistical inference was run in the form of a t-test to assess whether the performance of the indices is statistically significant against the JSE ALSI. This study finds evidence of herding behavior on the RESI10, INDI25, and FINI15 indices during the global financial crisis, and no herding behavior was documented during normal periods.

Key words: JSE, herding behavior, financial crisis
JEL Classification: G40

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1. INTRODUCTION

In the field of behavioral finance, herding behavior is known to influence investors' buying and sell decisions. Herding behavior is a mindset that is characterized by a lack of individual decision-making, causing investors to think and act in the same way as the majority of those around them (Bikhchandani et al., 2000). Alternatively, it can be defined as the tendency among investors to imitate the actions of other market participants (Angela-Maria et al., 2015). This kind of behavior has implications on investor trading, financing choices, managerial investment, market prices, and market regulation. Herding behavior entails different types of irrationality which reflects on why investors tend to follow what others do (Ouarda et al., 2013).

The theories underpinning this study on herding behaviour include: Efficient Market Hypothesis (EMH), which postulates that market participants cannot outperform the market in a consistent manner and earn abnormal risk-adjusted returns; the Random Walk Theory, which argues that stock price changes are independent of each other and as a result, the past trend of a stock price cannot be used to predict its future movement; the Morden Portfolio Theory(MPT), which is a passive portfolio management approach based on the portfolio risk-return profile for portfolio selection and construction: and Traditional finance, which is based on the MPT and EMH, claiming that investors think rationally and thus their financial decisions in pursuance of maximization of wealth for any given level of risk. These theories will be expanded on in the section on literature review (see below).

Studies on herding behaviour in the South African stock market focus on component indices, mutual funds, financial industry, and property industry found herding behaviour to be present (Ababio et al., 2017; Gilmour et al., 2002; Sarpong et al., 2014; Seetharam, 2013). This study deviates from empirical studies on the JSE by focusing on the JSE tradable sector indices, which are a representation of all the JSE listed instruments, classified according to their sector categories, namely, Resources (RESI10), Financials (FINI15), and Industrials (INDI25). The study focuses on three different market volatility periods in South Africa namely before, during, and after the global financial crisis period, adopting two major testing measures (cross-sectional absolute deviation of returns and cross-sectional standard deviation of returns) of herding behaviour by Christie et al. (1995) and Chang et al. (2000).

Thus, the current study aims to determine whether investors follow herding behavior based on the SA tradable sector indices, before, during and after the financial crisis.

2. LITERATURE REVIEW

The JSE is currently ranked the 17th largest stock exchange in the world in terms of market capitalisation as well as being the largest exchange in the African continent (JSE,

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2021). According to the Industry Classification Benchmark (ICB), the South African sector categorizes all listed instruments into one of three sectors, namely Resources, Financials, and Industrials, based on their revenue (JSE, 2017). The industrials index (INDI25) is comprised of the 25 largest industrial stocks by market capitalization; the financials index (FINI15) comprises of 15 largest financial stock by market capitalization, and the resources index (RESI10) comprises of the 10 largest resources stocks by market capitalization.

This section discusses the theoretical underpinnings of herding behaviour including the efficient market hypothesis (EMH), Random Walk Theory, and the Modern Portfolio Theory.

The Efficient Market Hypothesis (EMH) theory was introduced by Eugene Fama in 1960, which postulates that market participants cannot consistently outperform the market and earn abnormal risk-adjusted returns (Malkiel, 2003). EMH exists in three forms, namely, the strong, semi-strong and weak. The first form of market efficiency i.e., the weak form of EMH implies that the market is efficient, based on historical information. This form of EMH stresses on how trend analysis commonly used by technical analysts is ineffective because it cannot be used to predict and outperform the market. The second form of market efficiency, the semi-strong form states that all publicly available information concerning the prospects of a firm is reflected in the stock price. This information also incorporates the weak-form hypothesis. Semi strong form uses fundamental data on the company's product which includes quality of management, balance sheet structure, patents, earnings forecasts, and accounting practices amongst others. The third form of market efficiency, the strong-form, views the market as efficient, reflecting all information, both, public and private. It incorporates the weak-form EMH and the semi-strong form EMH (Fama, 1992). The strong-form suggests that corporate insiders and specialists have access to pertinent information long before it is publicly released, enabling insiders and specialists to gain from trading with this information.

The Random Walk Theory argues that stock price changes are independent of each other and as a result, the past trend of a stock price cannot be used to predict its future movement (Broadbent et al., 1953). Kendall (2021) further argues that stock prices follow a random walk because investors cannot predict the future market prices of a stock. Applying the RWT to finance and stocks suggests that a follower of the theory believes it is impossible to outperform the market without assuming additional risk.

The Morden Portfolio Theory, pioneered by H. Markowitz (1952) is a passive portfolio management approach based on the portfolio risk-return profile for portfolio selection and construction (Garaba, 2005; Vukovic et al., 2017). A combination of diversification for risk reduction and efficient capital markets increases the expected returns of a portfolio. By formalizing the concept of diversification, Markowitz suggests that investors should focus on selecting portfolios based on their joint risk-reward features instead of merely compiling individually attractive securities (Bera et al., 2008). Using past returns of each asset on a portfolio and statistical measures such as standard deviation and average return, the expected return and volatility of any portfolio are constructed. Markowitz uses volatility and expected return as proxies for risk and reward. H. M. Markowitz (1999), Mossin (1966), Sharpe (1964), and Lintner (1965) have all independently contributed towards the development of CAPM (Capital Asset Pricing Model) which is an extension of (H. Markowitz, 1952) portfolio theory. CAPM is a one-factor model which illustrates the relationship between risk and returns associated with assets within a given portfolio.

Behavioral finance models, introduced by De BONDT et al. (1985), developed in response to the need to explain investor behavior and market anomalies when rational models failed to provide sufficient explanations. The theory of behavioral finance tests the existence of overreaction in the market and found that investors systematically overreact to unexpected news resulting in weak-form inefficiencies in the stock market (Thaler, 2005). Several studies found that the behavior of market participants affects their investment decisions (Baker et al., 2010).

Traditional finance, which is based on the Modern Portfolio Theory (MPT) and EMH, argues that investors think rationally and thus their financial decisions result in a maximization of wealth for any given level of risk (Bodie, 2010). Behavioral finance relaxes the assumptions of investor rationality and investor risk aversion in the market as proposed by traditional finance. It recognizes the role of cognitive errors and emotions habitually influencing investors in their financial decisions. Behavioral finance emerged as a field that can explain some of the difficulties that traditional finance theory (EMH) is not able to explain.

In an attempt to explain investor irrationality, behavioral finance puts forth evidence of the psychology and biases that arise when investors are influenced by their individual beliefs (Barberis et al., 2005). Hodnett et al. (2012) assert that investors make decisions based on their emotions in addition to the mean, variance, and covariance of asset returns upon making investment decisions. Behavioral finance has led to further developments, the most notable of these being the theory of herding behavior.

Herding behavior is a branch of behavioral finance, which is a mindset that is characterized by the lack of individual decision-making, causing investors to mimic one another (Trueman, 1994) or replicate the behavior of other investors (Bikhchandani et al., 2000). In this way, the theory of herding behavior seeks to connect the traditional finance anomaly and behavioral finance anomaly relating to investors.

Herding behavior is mostly seen in periods of market extremes (Christie et al., 1995), probably as a result of social pressure and the common belief that the crowd cannot be wrong and knows better than individual investors (Hwang et al., 2001). Herding exists in two forms, namely unintentional and intentional herding. Unintentional herding happens due to simultaneous reaction to a common signal, the presence of this kind of herding behavior is a momentum investment (Clement et al., 2005). If herding behavior is driven by historical returns, this would be interpreted as evidence of unintentional herding (Froot et al., 1992; Sias, 2004). According to Kremer et al. (2013), intentional herding occurs whenever traders intentionally follow the crowd and ignore their private information or are not certain enough to make their own decisions, and therefore, they follow the crowd (Walter et al., 2006). This is a result of the belief that other investors possess superior information.

Investors follow herd behavior because of the social pressure of conformity as investors are sociable beings and have a natural desire to be accepted by other investors, and as a result following a group of investors is an ideal way of following herd behavior (Demirer et al., 2010).

More so, investors become part of a group and follow the herd when they know and feel that they cannot voice their own opinions alone (Kim et al., 2005). In this way, following a herd provides a sense of security to individual investors.

The following section discusses past studies that have been conducted on herding behavior in developed markets and developing markets during normal periods and periods of market volatility.

2.1 Herding Behavior in Developed Markets During Normal Periods

Normal periods are defined as market periods where security's value does not fluctuate dramatically. These periods are associated with low market volatility, which is measured statistically by beta. Shiller et al. (1989) study 250 stocks on the US market and found that herding is common in financial markets due to the presence of large institutional investors. Findings show that herding is subject to information on actions of investment professionals when they are buying and selling volatile stocks. Lobao et al. (2007) test the existence of herding behavior on the Portuguese mutual funds during the period from 1998 to 2000, using the measure of herding behavior suggested by Lakonishok et al. (1991), and found significant evidence of herding behavior for Portuguese mutual funds. These results indicate that the level of herding is stronger than the herding behavior that is found for institutional investors on the same stock market.

In addition, Walter et al. (2006) evaluate the trading activity of German mutual funds in the 1998–2002 periods to study whether mutual fund managers in Germany follow herding behavior. Periods of bull stock markets (January 1998 until March 2000) and the preceding bear market (April 2000 until December 2002) both point to the presence of herding behavior.

Agudo et al. (2008) analyze the presence of the herding behavior phenomenon in the management style of Spanish equity funds. Monthly returns data is collected for all Spanish equity funds investing in the domestic stock market from July 1994 to June 2002. This data is then assessed using the herding behavior measure by Lakonishok et al. (1991) and Sharpe (1964). Their results show significant evidence of herding behavior in the value stocks and growth stocks during the period of study. Hachicha (2008) study on the Toronto stock market, adopting the Dynamic Herding measure based on the cross-sectional dispersion of trading volume, proves the existence of herding behavior under different market conditions. Moreover, Rompotis (2018) study in the USA on Exchange-traded Funds (ETFs) over a period 2012-2016 demonstrates that herding is not the case for ETFs, as evidenced by the significant magnitude of the average return dispersion measures.

Recent studies by Mand et al. (2018) Ah Mand et al. (2021) on the determinants of herding behavior in the Malaysian stock market for Shariah-compliant, conventional stocks as wlel as the whole market of Malaysia found that the trading volume of the market determines the herding behavior for Shariah-compliant, conventional stocks and the broader market. Their study also reveals herding behaviour of investors among Shariah-compliant when the market is up and its non-linear relationship with the market return. Moreover, for conventional stocks, herding behavior is found to exist with a linear relationship during down market only and when considering the whole market sample, on-linear herding behavior only exists during down market; for the up market, herding behavior is found to have a linear relationship with the market return.

2.2 Herding Behavior in Developed Markets During Volatility Periods

Periods of market volatility are defined as market periods where security's value fluctuates dramatically. Christie et al. (1995) analyse market alternates between normal and extreme phases and seek to determine whether herding behaviour exists during periods of financial distress. The authors use daily and monthly data and show that when investors follow herding behaviour toward the market then individual asset returns will not diverge much from the overall market return. Christie et al. (1995) found that herding behavior is absent during the sample period, concluding that there is a high probability for investors to follow herding behavior in stressful markets as individual investors are likely to discard their own beliefs and follow the market consensus. Chang et al. (2000) extend the findings of Christie et al. (1995), using cross-sectional absolute deviations (CSAD) as a measure for dispersion. The authors examine the presence of the herding hypothesis in five financial markets including developing and developed markets. These financial markets are the US, Hong Kong, Japan, South Korea, and Taiwan. The authors conclude that herding is not present in developed (US & Hong Kong) economies but present in emerging economies (South Korea and Taiwan).

Moreover, Vieiraa and Pereirab (2014) study the presence of herding behavior on the European market, by evaluating the stocks that constitute the Portuguese stock PSI-20 index, for the period between 2003 and 2011. The authors use two methods to evaluate herding behavior; one of these applied a measure of herding, based on the methodology used in Chang et al. (2000), using CSAD measure, and the other applied a measure of herding based on the methodology used in Christie et al. (1995), which uses the CSSD measure. The authors like Vieiraa & Pereirab, (2014) found weak evidence of investor sentiment influencing herding.

Recent empirical studies show that herding behavior exists in the Taiwanese stock market and is consistent with the findings by Demirer et al. (2010), Chiang et al. (2013) and others also demonstrate how the herding behavior of investors is more severe during the financial crisis period of 2007–2008 than it is during normal periods (Wang et al., 2019).

2.3 Herding Behavior in Developed Markets During Normal Periods

Tan et al. (2008) study the presence of herding behavior in the Shanghai and Shenzhen Stock Exchanges (developing markets) from 1996 to 2003. They use the linear test by Christie et al. (1995) and the non-linear test by Chang et al. (2000) and found evidence of herding behavior in the Shanghai and Shenzhen markets for A-shares in the bull and bear phases. They also found strong evidence of herding behavior in the Shanghai market when there is high volatility and when markets are rising. In addition, evidence of herding over weekly and monthly time intervals is found to be much weaker, signifying that herding behavior is a phenomenon that is confined to short periods.

In their study, Lao et al. (2011) examine herding behavior in the Chinese and Indian stock markets, adopting the methodology of Christie et al. (1995) and Chang et al. (2000). Their findings suggest that herding behavior exists in both markets, and the level of herding depends on market conditions. In the Indian market, the study finds that it occurs during up-swings in market conditions whereas in the Chinese market, herding behavior is greater when the market is falling, and the trading volume is high.

Also, Angela-Maria et al. (2015) study herding behavior on the daily returns for the companies listed on stocks markets in Czech Republic, Poland, Hungary, Romania, and Bulgaria for the period from January 2008 to December 2010 and found evidence of herding behaviour of investors on all the stock markets, except for Poland, which is exhibited in both upward and downward trends. A study by Gilmour et al. (2002) on the South African stock market, using the herding behavior measure proposed by Lakonishok et al. (1991) to test institutional herding phenomenon in the unit trust

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industry (1992 to 1999), found the presence of comparatively low levels of herding behavior among institutional investors. The authors also document the highest level of herding on aggressive growth funds, suggesting a substantial positive connection existed between the risk profile of funds and the level of herding on the JSE, both, on the sell-side and the buy-side.

Later studies in the South African context by Seetharam (2013) observe herding behavior from 1995 to 2011, which encompasses both the bear and bull markets. It is found that herding behavior appears to dramatically fluctuate before a market contraction. They (Seetharam, 2013) found evidence that a negative market reaction is led by an increase in herding during a South African market contraction (bear market) can thus impact financial forecasts and volatility estimates of the market. Another study in South Africa, based on the financial and real estate sectors, by Ababio et al. (2017), for the period January 2010 to September 2015, found the presence of herding behavior in the banking during the bear phase i.e., when the market is falling while the real estate sector investors show herding behavior to be present during bull phase i.e., when the market is rising.

2.4 Herding Behavior in Developing Markets During Periods of Market Volatility

Kaminsky et al. (1999) analyze the type of news that move the markets in days of market jitters on the Malaysian Stock exchange and found the presence of herding behavior during the period of financial reforms in Malaysia.

Tan et al. (2008) study on the Shanghai and Shenzhen Stock Exchanges, from 1996 to 2003 finds evidence of herd behavior in the bull and bear phases for A-shares. In their study, Lao et al. (2011) examined herding behavior in the Chinese and Indian stock markets. In the Indian market, the study finds that it occurs during up-swings in market conditions whereas in the Chinese market, herding behavior is greater when the market is falling, and the trading volume is high.

Moreover, Messis et al. (2014) investigate the presence of herding in the Athens Stock Exchange over the 1995-2010 period and their findings show the presence of herding on all volatility measures considered. Angela-Maria et al. (2015) investigate the existence of herding behaviour of investors from emerging markets on stock markets of the following countries: Czech Republic, Poland, Hungary, Romania, and Bulgaria, for the period from January 2008 to December 2010. They found evidence of herding behaviour of investors on all the stock markets, except for Poland. Moreover, a study by Zafar et al. (2016) finds that there is a presence of herd behavior during both up and down-market conditions in the stock market of Pakistan.

In the South African context, Seetharam (2013) study herding behavior together with market cycles from 1995 to 2011 which encompasses both, the bear and bull markets. In this regard, Seetharam (2013) use three different methods proposed by Christie et al. (1995), Chang et al. (2000), and Hwang et al. (2001) to analyze their data and found evidence that a negative market reaction is led by an increase in herding during a South African market contraction. Ababio et al. (2017) study conducted in the context of South Africa's financial industry on stock returns on the JSE from January 2010 to September 2015 found the presence of herding behavior in banking during the bear phase.

Even though there is extensive literature on the subject, empirical studies on the JSE remain limited. The documented findings on the JSE are consistent with other related studies on developed markets for example studies by Lakonishok et al. (1991); Chang et al. (2000); Tan et al. (2008). It is evident from the above studies on the JSE that there is no existing literature on herding behavior which focuses on the JSE tradable indices. This research study seeks to fill this gap with a view to contribute to the existing literature on herding behavior in the context of the JSE. Moreover, most prior research on herding behaviour concentrates on the developed markets or some of the prominent emerging markets, who are often categorised as speculators and their trading causes significant market volatility. Therefore, it is worthwhile to investigate whether speculative investors will enhance potential herding behaviour. Also, South Africa has experienced a series of episodes of financial, natural, and political crises, bringing volatility and uncertainty to a high level.

This paper will contribute to the herding literature in number of ways. First, this research will build on the behavioural research on investors' herding to equity markets in South Africa. Second, this research is the first study that investigates investors' trading behaviours around multiple points and different kinds of crises situations. Finally, even though ETFs or tradeable indices have been consistently attracting considerable attention from both, retail and institutional investors worldwide, the possible herding patterns in their trading behavior remain understudied.

3. RESEARCH METHODOLOGY

This study applied the cross-sectional standard deviation of returns (CSSD) measure postulated by Christie et al. (1995), and the cross-sectional absolute deviation of returns (CSAD) measure proposed by Chang et al. (2000) to examine if there was evidence of herding behavior on the JSE tradable indices (RESI10, INDI25, FINI15). The CSSD and CSAD herding behaviour measures have been tested and validated in past literature (Angela-Maria et al., 2015; Chang et al., 2000; Tan et al., 2008). This section describes the research design, highlights methodological issues involved such as sample data, and outlines the techniques of data analysis employed in the study.

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There are approximately 300 tradable indices and sub-indices on the JSE (JSE, 2018). The top JSE indices comprise of the Top 40, JSE ALSI (which include some 150 JSE-Listed companies and the largest index in terms of size and overall value (JSE, 2018), the industrials index (INDI25) constitutes of 25 largest industrial stocks by market capitalization, the financials index (FINI15) comprises 15 largest financial stock by market capitalization and lastly, the resources index (RESI10) which represents the 10 largest resources stocks by market capitalisation. The study sample thus is comprised of the three indices that constitute the JSE tradable sector, namely the INDI25, FINI15, and RESI10 indices.

The period under consideration for the study was from 1 January 2007 to 31 December 2017 (132 months). This period was selected because of the different market phases experienced during this time due to the global financial crisis of 2008, the continuous fluctuations of interest rates, and the devaluation trends of the South African Rand (ZAR) against the United States Dollar (U.S Dollar).

Daily data was used in the study, as obtained from Bloomberg, a website that provides a comprehensive and continuously updated information resource. Daily closing prices for each of the four indices, including the JSE ALSI, were downloaded to compute the daily returns and volatilities. Each of the three tradable sector indices had a base date of 24 June 2002. The data collected from Bloomberg included the historical price records for the three indices, namely INDI25, FINI15, and RESI10. The study period was divided into three periods, starting with the period from 1 January 2007 to 30 June 2007, which was before the global financial crises, then the period from 1 July 2007 to 31 August 2009, which was the period during the global financial crisis, and lastly from 1 September 2009 to 31 December 2017 which was the period after the global financial crises.

This study used Microsoft Excel and Stata V to run the estimations and calculate the CSSD and CSAD for 132 months (11 years). Daily downloaded stock prices for each index were arranged in ascending order based on dates and the average rate of return and standard deviation for each index were then estimated for the four indexes which include RESI10, INDI25, FINI15, and JSE ALSI. Using the same daily data, the average return dispersion and standard deviation of dispersion were estimated. With that in mind, this research used the volatility and average rate of return estimates together with a dummy to calculate the CSSD and CSAD values as used by other scholars such as, Angela-Maria et al., (2015), Vieiraa & Pereirab, (2014) and Christie et al. (1995), who used CSSD as a measure of the average proximity of individual asset returns to the realized market average to test herding behaviour.

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To evaluate the existence of herding within the INDI25, FINI15, and RESI10 indices, the level of dispersion was calculated for indices portfolios and its effects of herding on market volatility.

To quantify the dispersions of individual returns from the market return, this research used CSSD which is the difference between an INDI25, FINI15, and RESI10 share's return and the market return. To test for herding behaviour pre- and post-financial crisis, the dispersion of equity returns, CSSD, was measured by the following expression:

$$(\mathrm{CSSD})^{\cdot} = \sqrt{\sum_{n=1}^{n}} \left(\frac{\mathrm{Ri}-\mathrm{R}}{\mathrm{N}-1}\right)^{.2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

where i and r is the cross-sectional average of the n returns in the portfolio and Ri is the observed return of INDI25, FINI15, and RESI10. This measure incorporates key attributes of herding behaviour by quantifying the degree to which asset returns tend to rise and fall in comparison with portfolio returns. Dispersions are expected to be low when herd behaviour is present and when dispersions are high, it implies that herding behaviour will be absent (Damodaran, 2012).

To test the presence of herd behavior on the JSE tradable indices during periods of market uncertainty, this research used Christie and Huang's (1995)'s formula, as provided below.

$$\mathrm{CSSD} = \partial + \beta^{\mathrm{L}}\mathrm{D}^{\mathrm{L}} + \beta^{\mathrm{X}}\ \mathrm{D}^{\mathrm{X}} + \mathrm{e}_{\mathrm{t}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

Where D^L = 1 if the market return on day t lies in the extreme lower tail of the return distribution

D^L = 0 otherwise, and D^X = 1 if the market return on day t lies in the extreme upper tail of the return distribution D^X = 0 otherwise. The ∂ coefficient denotes the average dispersion of the INDI25, FINI15, and RESI10 excluding the regions covered by the two dummy variables. This research used 95% confidence intervals in distributions to define extreme market price movements as done by Christie et al. (1995).

The second return dispersion methodology employed in this paper was suggested by Chang et al. (2000) who used the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion. According to Chang et al. (2000), CSAD shows that rational asset pricing models also predict that there is a linear relation between equity return dispersions and market return. The relationship is non-linear when investors follow aggregate market behaviour during periods of large average price. CSAD is expressed as

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$$\text{CSAD} = \frac{1}{N} = \sum_{i=1}^{n} \left|\beta i - \beta m\right| (\text{Rm} - \text{rf})_{\ i,t} \ldots\ldots 3$$

Where βm is the systematic risk of an equally weighted market portfolio, rf is the return on INDI25, FINI15, and RESI10 with the zero-beta portfolio, and βi is the time-invariant systematic risk measure of the security *i* range 1 . . . *n* and *t* 1 . . . .*t*

To capture any possible non-linear relation between security return dispersions and the market return, Chang et al. (2000) proposed an alternate test of herding and used an additional regression parameter. To measure the possibility that the degree of herding may be asymmetric in the up-versus the down-market, the following formulae were used

$$\text{CSAD}^{\text{UP}}/\text{t} = \text{a} + \gamma 1^{\text{up}}\text{R}^{\text{UP}} + \gamma 2^{\text{up}}\,(\text{R}^{\text{UP}})^2 + \text{E}^{\text{t}}) \ldots\ldots 4$$

$$\text{CSAD}^{\text{DOWN}}/\text{t} = \text{a} + \gamma 1^{\text{DOWN}}\text{R}^{\text{DOWN}} + \gamma 2^{\text{DOWN}}\,(\text{R}^{\text{DOWN}})^2 + \text{E}^{\text{t}}) \ldots\ldots 5$$

Where CSAD is the average absolute value of the deviation of each stock relative to the return of the INDI25, FINI15, and RESI10 equally weighted market portfolio, *R* in period *t*, and R^{DOWN} and R^{UP} is the absolute value of an equally weighted realized return of INDI25, FINI15, and RESI10 on day *t* when the market is up (down). Both variables were computed daily. When herding behaviour is present during periods of large price movements then there is expected to be a less proportional increase or decrease in the CSAD measure.

4. FINDINGS AND DISCUSSION

This section presents the findings in the form of tables seeking to depict whether evidence of herding behavior existed before the global financial crisis, during the global financial crisis, and after the global financial crisis or not.

A total of 50 stocks were considered comprising 25 largest industrial stocks by market capitalization, 15 largest financial stock by market capitalization, and 10 largest resources stocks by market capitalization. The daily closing prices for RESI10, INDI25, FINI15, and JSE ALSI from January 2007 to December 2017 were used (in total, 2,751 days were observed).

Since the study period was divided into three categories, starting with the period from 1 January 2007 to 30 June 2007 (in total, 124 days were observed) which was before the global financial crises, then the period from 1 July 2007 to 31 August 2009 (in total, 293 days were observed) which was the period during the global financial crisis and lastly,

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from 1 September 2009 to 31 December 2017 (in total, 2,334 days were observed) which was the period after the global financial crises.

4.1 Descriptive Statistics Before the Global Financial Crisis

This section provides the results of estimates for mean, average dispersion, the mean and standard deviation of the tradable indices before the global financial crisis. Table 1 provides the estimates of the mean, standard deviation, average return dispersion, and standard deviation dispersion for RESI10, INDI25, FINI15, and JSE ALSI before the global financial crisis (January 2007 up to end of June 2007).

The RESI10 index yielded daily returns of 0.13 per cent with a standard deviation of 0.01475, the INDI25 index had an average daily return of 0.11 per cent while its standard deviation was 0.01879 and, the FINI15 index had the highest performance with an average daily return of 0.16 per cent, and a standard deviation of 0.01989. The JSE ALSI, used as a benchmark of the market, had an average return of 0.10 per cent with a standard deviation of 0.01312.

Table 1: Average Daily Returns and Standard Deviations Before the Global Financial Crises

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion
FINI15	0,16%	0,340%	0,01989	0,0140%
RESI10	0,13%	0,934%	0,01475	0,0025%
INDI25	0,11%	0,515%	0,01879	0,0018%
JSE ALSI	0,10%	0,410%	0,01312	0,0011%

From these results, it can be deduced that the RESI10, INDI25, FINI15, and JSE ALSI indices, performed better than the market (JSE ALSI) before the global financial crisis. The FINI15 index had the highest standard deviation implying that if an investor had invested in the FINI15 index as individual security, a great loss or profit could have been incurred. This was a result of the high risk that was associated with this index before the global financial crisis.

4.2 Descriptive Statistics During the Global Financial Crisis

Table 2 below provides the estimates of the mean, standard deviation, average return dispersion, and standard deviation dispersion for RESI10, INDI25, FINI15, and JSE ALSI during the global financial crisis (July 2007 up to end August 2009), in total 293 days were observed. The RESI10 index yielded the highest daily returns of 0.1572 per cent with a standard deviation of 0.0147, an average return dispersion of 0,053 per cent, and a standard deviation of dispersion of 0.0025 per cent. The INDI25 index recorded an average daily return of 0.0528 per cent while its standard deviation was 0.0081 with an average return dispersion of 0.0511.and a standard deviation of dispersion of 0.0018 per cent. In addition, the FINI15 index had the lowest mean with a daily return of (0.0127) percent, a standard deviation of 0.0118, an average return of dispersion of 0.047 per cent, and a standard deviation of dispersion of 0.0124 per cent. The market as represented by the JSE ALSI had an average return of 0.1027 per cent with a standard deviation of 0.0121 an average return of dispersion of 0.0183 per cent and a standard deviation of dispersion of 0.1200 per cent.

As recorded in Table 2, the FINI15 index had the lowest performance during the global financial crisis compared to other indices. Also, the results show that during the global financial crises period, only the RESI10 index outperformed the market.

Table 2: Average Daily Returns and Standard Deviations During the Global Financial Crises

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion
FINI15	0,0127%	0,0470%	0,0118	0,0124%
RESI10	0,1572%	0,0530%	0,0147	0,0025%
INDI25	0,0528%	0,0511%	0,0081	0,0018%
JSE ALSI	0,1027%	0,0183%	0,0121	0,1200%

4.3 Descriptive Statistics After the Global Financial Crisis

Table 3 provides the estimates of the mean, standard deviation, average return dispersion, and standard deviation dispersion for RESI10, INDI25, FINI15, and JSE ALSI after the global financial crisis (1 September 2009 to 31 December 2017).

Table 3: Average Daily Returns and Standard Deviations Post the Global Financial Crises

Index	Mean	Average return dispersion	Standard deviation	Standard deviation of dispersion
FINI15	0,0793%	0,0250%	0,0117	0,0140%
RESI10	0,0033%	0,0750%	0,0158	0,0001%
INDI25	0,0717%	0,0860%	0,0097	0,018%
JSE ALSI	0,040%	0,0920%	0,0093	0,020%

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As shown in Table 3, the performance of the FINI15 index during the post-global financial crises was 0.0793 per cent for the mean, with a standard deviation of 0.0117, an average return dispersion of 0,025 per cent, and an average return dispersion of 0.025 per cent. The RESI10 index had a mean of 0.0033 per cent, a standard deviation of 0.0158, an average return dispersion of 0,075 per cent, and a standard deviation of dispersion of 0,0001 per cent. In addition, the INDI25 index recorded a mean of 0.0717 per cent, a standard deviation of 0.00997, a standard deviation of dispersion of 0,018 per cent, and an average return of 0,086 per cent. Lastly, the JSE ALSI index recorded a mean of 0.040 percent, a standard deviation of 0.0093, a standard deviation of dispersion of 0.020 per cent, and an average return of 0,092 per cent.

In summary, the findings recorded in Table 2 and Table 3, show that the mean return of the FINI15 index improved during and post the global financial crises period from 0.0127 percent to 0,0793 percent implying that investors in this index earned better returns after the global financial crisis. On the contrary, the RESI10 index performance in terms of return declined from 0.1572 percent to 0.0033 percent. The INDI25 index still maintained the lowest level of risk with a standard deviation of 0.00997. In this regard, after the global financial crises, both the FINI15 index and the INDI25 index performed above the JSE ALSI which had a return of 0.040 percent and 0.0093.

4.4 Descriptive Statistics for The Entire Study Period

This section provides the results of estimates for mean, average dispersion, the mean and standard deviation of the tradable indices for the entire period understudy.

Table 4 provides the estimates of the mean, standard deviation, average return dispersion, and standard deviation dispersion for RESI10, INDI25, FINI15, and JSE ALSI for the entire period of study i.e., from January 2007 to December 2017.

Table 4: Average Daily Returns and Standard Deviations for the 11year Period of Study

Index	Mean	Standard deviation	Coefficient of variation
FINI15	0,035%	0,0145	0,414
RESI10	0,011%	0,0195	0,178
INDI25	0,060%	0,0113	0,188
JSE ALSI	0,040%	0,0122	0,305

The INDI25 index had a return of 0.060 per cent with a standard deviation of 0.0113 and a coefficient of variation of 0.188. The FINI15 index had a mean of 0,035 per cent with a standard deviation of 0.0145 and a coefficient of variation of 0.414. The RESI10 index had a mean of 0.011 per cent and a coefficient of variance of 0.178 with a standard deviation of 0.0195 and finally, the JSE ALSI index had a mean of 0,04 per cent with a coefficient of variation of 0.305 and a standard deviation of 0.0122.

Overall, the INDI25 index had the highest performance while maintaining a low level of risk. The FINI15 index performed moderately compared to the JSE ALSI, having the highest risk (CV of 0,414) and the RESI10 index had the lowest performance.

The next section discusses the CSSD measure results of the three indices against the JSE ALSI index which is used as a benchmark for the four periods (before, during, after, and the entire period).

4.5 Herding Behaviour on The JSE Tradable Indices

The Cross-Sectional Standard Deviation (CSSD) measures dispersion, which refers to the spread between the market and in this case, an index return. As such, CSSD is the dispersion between the JSE ALSI returns and RESI10, INDI25, and FINI15 independently. Herding behavior is absent when the dispersion between the JSE ALSI and the indices (RESI10, INDI25, and FINI15) is negative (Christie et al., 1995).

4.6 CSSD Before the Global Financial Crisis

This section provides the results of estimates for CSSD of the JSE tradable indices before the global financial crisis. Table 5 provides the estimates of βL and βu for RESI10, INDI25, FINI15, and JSE ALSI indices at the 95 per cent confidence interval for the period before the global financial crisis.

Table 5: CSSD For the Period Before the Global Financial Crises

Using ALSI	**95% Confidence**		
	a	βL	Bu
FINI15	0,0018	-0,00261	-0,0028736
RESI10	0,0003	-0,00031	-0,0003339
INDI25	0,0061	-0,00018	-0,0090880

From Table 5, the estimates of βL for FINI15, INDI25, and RESI10 are -0.002613, -0.000315, and -0.000189, respectively and the estimates of βu are -0.00287368 for FINI15, -0.00033395 for INDI25 and -0.00908805 for RESI10. Since all coefficients of βu and βL are negative at 95 per cent confidence interval, it implies that herding behavior was absent. These results are in contradiction with the predictions of herding behavior but consistent with the predictions of rational asset pricing, as documented by Christie et al. (1995). This means that herding behavior was not present before the global financial crisis. These results are consistent with the findings of Prosad et al. (2012) which indicate that no evidence of herding behaviour was found on the Indian Stock Market over the period 2006 to 2011.

4.7 CSSD During the Global Financial Crisis

This section provides the results of estimates for CSSD of the JSE tradable indices during the global financial crisis. Table 6 provides the estimates of βL and βu for RESI10, INDI25, FINI15, and JSE ALSI indices at the 95 per cent confidence interval for the period during the global financial crisis.

Table 6: CSSD for the Period During the Global Financial Crises

Using ALSI	**95% Confidence**		
	a	βL	Bu
FINI15	0,0738	0,002613	0,00287368
RESI10	0,0623	0,07505	0,00433395
INDI25	0,0574	0,01905	0,00790588

As noted in the table, the estimates of βL and βu have positive coefficients ranging from the lowest value of 0,01905 under βL for the RESI10 index to the highest of 0,07505 for the INDI25 index. The CSSD has been increasing, implying that herding behavior was present. The reason for the increase could be either that investors may be following herding behavior towards the market portfolio or a group of investment experts. During periods of high market volatility, investors' emotions tend to increase as well as the fear of missing out on good investments. With that in mind, this can lead investors to follow herding behavior in search of a form of reassurance (Seetharam, 2013).

4.8 CSSD After the Global Financial Crisis

This section provides the results of estimates for CSSD of the JSE tradable indices after the global financial crisis. Table 7 provides the estimates of βL and βu for RESI10, INDI25, FINI15, and JSE ALSI indices at the 95 per cent confidence interval for the period after the global financial crisis.

Table 7: CSSD For the Period After the Global Financial Crises

Using ALSI	**95% Confidence**		
	a	βL	Bu
FINI15	0,018	-0,00261	-0,0028736
RESI10	0,013	-0,00758	-0,0085008
INDI25	0,009	-0,00433	-0,0053176

As shown in the table, the estimates of βL are -0.002613 for INDI25, -0,00758 for FINI15, -0,00433 for RESI10. Also, the estimates for βu are -0.0028736 for FINI15, -0,0085008 for INDI25, and -0,0053176 for RESI10. The estimates for both βL and βu

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have negative coefficients implying that herding behavior was absent after the global financial crisis period.

4.9 CSSD for the Entire Period of Study

This section provides the results of estimates for CSSD of the JSE tradable indices for the entire period of study. Table 8 provides the estimates of βL and βu for RESI10, INDI25, FINI15, and JSE ALSI indices at the 95 per cent confidence interval for the period understudy.

Table 8: CSSD for the 11 Years of Study

Using ALSI	**95% Confidence**		
	a	βL	Bu
FINI15	0,028	0,0002613	0,000287368
RESI10	0,003	0,0003941	0,000433395
INDI25	0,041	0,0007189	0,000790588

These results show that βL have positive estimates of 0.0002613, 0.0003941, and 0.0007189 for FINI15, INDI25, and RESI10 respectively. βu also had positive estimates of 0,000287368, 0,000433395, 0,000790588. This implies that overall herding behavior was present on the JSE tradable indices, however, it was seen to be particularly dominant during periods of high market volatility, in this case during the global financial crisis.

The overall findings on herding behavior are similar to what was documented by Angela-Maria et al. (2015) during the period January 2008 to December 2010 on the Central and South-Eastern Europe: Czech Republic, Poland, Hungary, Romania, and Bulgaria stock markets. It is essential to note that during periods categorized as normal phases, investors' actions can be described by the modern finance theory. In other words, investors would follow their own beliefs, however, during periods described with high market volatility, investors' emotions tend to increase (Seetharam, 2013). As a form of reassurance investors then follow the investment decisions of their peers. Conversely, Lao et al. (2011) show that herding behavior existed in both, periods of high and low market volatility.

In comparing ALSI and the RESI10 returns for the entire period of study, the RESI has been mostly outperforming the JSE ALSI index returns. The dispersions between the two indexes ALSI and RES were not very substantial. It was found that the dispersions were high during the period between 2008 and 2009 which was during the global financial crisis. For most periods during the period of study the JSE ALSI returns were above that of the INDI25 index, and also the dispersion between the two was not very substantial.

The FINI15 index returns have been higher than JSE ALSI index returns from 2014 to 2018 consistently. On the contrary, during the period 2007 to 2013, the JSE ALSI index returns were above that of the FINI15 index.

In brief, herding behavior was visible during the global financial crisis i.e., during the period of high market volatility. These findings are consistent with what was recorded by Ah Mand et al. (2021); Jirasakuldech et al. (2021); Ababio et al. (2017); Angela-Maria et al., (2015); Sarpong et al., (2014); Lao et al., (2011).

5. CONCLUSION

This paper aimed to provide evidence of herding behavior on the JSE limited tradable indices which include RESI10, INDI25, and FINI15 before, during, and after the global financial crisis for the period from January 2007 to December 2017. After calculating the CSSD and the CSAD for each period, no herding behaviour was recorded by both measures before the global financial crisis. During the global financial crisis, herding behaviour was found to be present on all the indices. During the post-global financial crisis herding behaviour was found to be present on the FINI index. Conversely, no herding was recorded on the RESI and INDI indexes post-global financial crisis. Overall, this research found that investors followed herding behaviour during periods of market volatility, and on the other hand no herding behavior was documented during normal periods.

Results of the herding behavior indicate the level of market efficiency; therefore, policymakers can trace the market efficiency through herding behavior. Policymakers and other stakeholders, therefore, should be able to adopt suitable policies to lead the market toward more efficient points by monitoring and enhancing the quality of information transmission. Investors, on the other hand, could also benefit from the results on their choice of an optimal portfolio to enhance the return of their investment. The JSE is of the view that, in line with the trading statement approach on DPS (distribution per share), at the very least, any difference of at least 15% from each or both of these elements (distributable income and the percentage of distributable income declared) is likely to be price-sensitive and should be announced. Thus, the implementation and enforcement of these guidelines should mitigate herding behavior on the JSE. The JSE could perhaps adopt the evaluation system used on the Taiwan Stock Exchange i.e., the Information Disclosure and Transparency Ranking System (IDTRS). The evaluation system uses information that listed companies entered into the Market Observation Post System and disclosed on their corporate website as the basis for its evaluations. The evaluation five main areas, including compliance, information timeliness, financial forecasting, annual reports, and website information disclosure. Each area included encompasses mandatory or voluntary disclosure indicators. By including these two types of indicators, investors were able to better interpret the evaluation results, as well as incentivize companies to elevate the quality of their disclosures to international standards. A study by Wang and Huang (2019) finds that the promotion of IDTRs of the financial supervisory institution has a positive influence on the financial market and states that the management could mitigate the irrational shock of stock prices by enhancing the transparency of the corporations.

This study recommends that future research can be conducted using data sets of volume and volatility measures, as opposed to only returns, as used in this study. Moreover, other recent measures of herding behavior such as the quantile regression model can be evaluated to determine if the results will be consistent with the first measures of herding behavior by Christie et al. (1995) and Chang et al. (2000).

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