Investors' Fear and Herding in the Johannesburg Stock Exchange (JSE)

By

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Abstract

Investors herd when they follow the investment decisions of other market participants and ignore their own private information, causing asset valuations to deviate from their fundamentals. This paper examines herding in the South African equity market by examining the impact of investor fear on herding behavior, using a survivorship-bias free daily dataset of companies within the JSE All Share Index over the period: 3 May 2002 to 31 December 2019. Using the cross-sectional absolute deviation (CSAD), this study examines market-wide herding behavior over multiple sub-periods, which consists of before, during and after the global financial crisis of 2007/08. The results suggest no evidence of herding towards the market return; on the contrary there is evidence of *'anti-herding'* behaviour during periods of market stress. However, there is significant herding towards the domestic fear index, which becomes more pronounced during the crisis period. Furthermore, investor herd behaviour appears to be sensitive to spill-over effects from the US investor fear-gauge, suggesting interconnectedness with global financial markets. Therefore, these findings suggest that fear plays an important role in enforcing irrational behaviour.

Keywords: Herd behaviour, return dispersion, JSE, financial crisis, investor fear, SAVI and VIX.

1. Introduction

Investor herding in the behavioral finance literature refers to the correlation of investors' trading behavior, as they mimic the actions of other market participants whilst ignoring their own personal information. This type of behaviour is often used to describe asset valuations that cannot be solely explained by fundamentals during periods of market stress. These market anomalies challenge traditional finance theory assumptions of rationality as investors' behaviour are ex-post characterised as irrational.

The examination of herding behaviour is important for both regulators and investors, as herding may destabilise financial markets, especially during crisis periods (Demirer & Kutan, 2006). Herding causes asset returns to become more correlated, making risk reduction via portfolio diversification less attainable for investors, as a greater amount of assets will have to be held in order to achieve their desired reduction in idiosyncratic risk. Some economists postulate that herding may lead to stock market bubbles, creating large disparities between a company's stock price and intrinsic value, which leads to inefficient price discovery in the market (Spyrou, 2013).

Existing literature suggest that herding is compounded by investor emotions such as fear, as this may result in investors ignoring their private information as they seek the comfort of the consensus opinion (Spyrou, 2013). This anomaly was documented in the seminal work of Christie and Haung (1995) and Chang et al. (2000), who argued that asymmetric herding behaviour in financial markets might be due to investor fear. This was based on the premise that herding was observed to be more statistically significant during periods of decreasing market returns relative to increasing market returns. However, the theoretical literature on how individuals behave under uncertainty is conflicting (Aharon, 2020). According to Forgas (1995), a positive mood reduces risk aversion while a negative mood increases risk aversion. This would mean that herding should be more pronounced in an environment of increasing fear (Aharon, 2020). On the other hand, according to the mood maintenance hypothesis, individuals with a positive mood will act more cautiously in order to maintain their positive mood (Isen & Patrick, 1983; Isen & Labroo, 2003). This would mean that herd behaviour should be more pronounced when the level of fear in the market is decreasing (Aharon, 2020).

Although investor sentiment is not easily quantifiable, recent studies have utilised the Chicago Board Options Exchange (CBOE) implied volatility index (VIX) as a proxy for US investors' fear and thus examine its impact in stock markets for example, Philippas et al. (2013), Huang & Wang (2017) and Economou et al. (2018). A domestic equivalent index is the South African Volatility Index (SAVI), launched in 2007 by the Johannesburg Stock Exchange (JSE), as a forward-looking index to measure the market's anticipation of 3-month market volatility (Tafou, 2014). When investors' anxiety and uncertainty around future market opportunities increases, they tend to adopt portfolio insurance strategies, causing the price of out-of-the money put options to rise, increasing the implied volatilities. That is why the VIX and SAVI are known as investor fear gauges (Whaley, 2009; Tafou, 2014). However, research on the effects of fear on herding behavior has mostly been limited to developed markets, due to the lack of well-established derivative markets.

Literature on herding in South Africa remains scarce with mixed results. Ababio and Mwamba (2017), restricted their analysis to only the South African financial industry and found no evidence of herding in the overall industry, except during bull markets. They also analysed the four sectors of the financial industry (banking, general financials, insurance and real estate) and found herding to be present in only the banking and real estate sectors. However, this paper does not examine the impact of the global financial crisis on South Africa's financial industry. By using an Autoregressive Distributed Lag (ARDL) model Niyitegeka and Tewari (2015), finds herding to be a short-lived phenomenon on the JSE, but the analysis is limited to only one hundred (100) stocks. Moreover, Seetharam and Britten (2013) examined herding using monthly data and found it to be absent overall, but present during bear periods. When analysed alongside the South African market cycle, herding was found to be present during periods of market instability. However, none of these papers make any attempt to control for survivorship bias in the data. This is important because using data that suffers from survivorship bias may lead to overly optimistic results in favour of herding (Seetharam and Britten, 2013).

A study by Muller and Ward (2011), shows that the percentage of "active share"[1] on the JSE decreased from around 50% in 1988 to 15% in 2001, and it remained around this range up to 2010. This indicates that fund managers are becoming less inclined to take positions that deviate from the index which should encourage herd behaviour. This makes the South African

[1] This refers to the proportion of a fund which differs from the benchmark index (Cremers & Petajisto, 2009).

market a good candidate to test the hypothesis that investors herd during periods of market stress.

Therefore, this paper contributes to the existing debate on investor herd behaviour in South Africa. This is done by examining the return dispersion of JSE stocks from the market return by using the classical cross-sectional absolute dispersion (CSAD) model, as developed by Chang et al. (2000), to examine market-wide herding behaviour during periods of market stress. One of the most significant shocks experienced in financial markets is the global financial crisis of 2007/8; which undoubtably contributed to investor fear. To understand this better this study examines herd behaviour before, during and after the global financial crisis. In order to analyse its effect, this paper follows the approach by Economou et al. (2018), who augments the CSAD model with the fear gauge, that is, the implied volatility index. Therefore, the main objective of this paper is to examine the impact of fear on investor herding behaviour on the JSE by looking at the periods before, during and after the global financial crisis.

To examine the above, this paper uses a survivorship-bias free dataset of daily returns of all companies on the JSE All Share Index (ALSI), over the period: 3 May 2002 to 31 December 2019. The SAVI is used to measure the impact of domestic investor fear on herding - while the incorporation of the VIX is used to provide potential insights on the spill-over effects of US investor fear into South Africa; since South Africa is often considered a major attraction for investors who want to invest in Africa and is a gateway to other emerging markets. Moreover, in an independent report for National Treasury, Thomas (2017), shows that foreign ownership of JSE listed companies have risen from 28% in 2008 to 38% in 2016. This provides for the opportunity to test the hypothesis that fear in international markets will spill-over into markets that are globally interconnected and cause investors to herd. This paper also seeks to investigate herding asymmetry by analysing the impact of fear during different market conditions by dividing the sample into different sub-periods. Therefore, the justification/significance of this paper is that it investigates the impact of both domestic and international fear on market wide herding on the JSE, using a survivorship-bias free dataset that captures the before, during and after periods of the global financial crisis, which is a first in the South African literature.

This article is structured in the following way: Section 2 provides a brief overview of the literature. Section 3 describes the data and methodology used to examine herding behaviour.

Section 4 reports and discusses the empirical results under the benchmark and augmented ordinary least squares (OLS) method during different sub-periods, while section 5 concludes.

2. Literature Review

It is important to understand that in the relevant literature there is no single definition of what herding is, as these theoretical models distinguish between agents that are (near)rational and irrational (Spyrou, 2013). Scharfstein and Stein (1990), argue that in a labour market with imperfect information managers may engage in rational herding behaviour in order to protect their reputations to avoid being singled out when things go wrong. Trueman (1994), finds similar behaviour among security analyst, by revealing that their earnings forecasts do not differ much from prior earnings expectations, even when their private information justifies more extreme forecasts. These efforts to bolster or preserve one's reputation emanates from principal-agent concerns (Devenow & Welch, 1996).

Another form of rational herding is through informational cascades, where investors gain valuable information from observing the actions of previous agents, which leads them to ignore their own private information (Bikhchandani et al., 1992). On the other hand, studies like Shleifer and Summers (1990), suggest that shifts in investor sentiment appear to be irrational and not driven by market fundamentals when these investors react to pseudo-signals like following the advice of "financial gurus".

By analysing the portfolio holdings of 341 money managers Lakonishok et al. (1992), find that pension managers would purchase and sell identical stocks as other managers. However, Wermers (1999), finds evidence of herd behaviour in small stocks by mutual fund investors but fairly low levels of herding in the trades of average size stocks. Although these arguments explain what is happening on the individual level, it does not explain why during periods of market stress asset returns on an aggregate level do not follow rational asset pricing models.

In a review of the herding literature Spyrou (2013), finds that the presence of herding on an aggregate level provides contrary evidence to the efficient market hypothesis (EMH). The EMH is the standard orthodox in the financial economics literature, which has been used as the foundation in many financial models (e.g. CAPM) to explain how financial markets operate (Malkiel & Fama, 1970). It assumes that markets are efficient and investors are rational. This implies that all available information regarding an individual stock is already incorporated into its share price, which means all stock prices reflect their intrinsic value.

It is for this reason that most economic scholars argue that herding occurs when investors are influenced by their emotions and not by market fundamentals, which makes their behavior irrational (Bekiros et al., 2017). Keynes (1936), postulates that in an environment of uncertainty and fear, individuals are dominated by their instincts, and their actions are dictated by their sentiment and hence act irrationally. These emotional biases are highlighted in McQueen et al. (1996), who finds that investors respond slowly to good news but react more quickly to bad news. Their research suggest that this type of behavior creates a greater incentive for investors to herd during periods of market stress. In other words, investors may fear the potential losses during bear markets more than the potential gains during bull markets.

To test for the presence of herding in the U.S. stock market, Christie and Huang (1995), developed a model which looks at the dispersion of individual equity returns from market returns during periods of market stress[2]. The reason being that according to rational asset pricing models, such as CAPM, individual assets differ in their sensitivity to market returns, which should cause dispersions to increase during periods of large price movements. Since investors suppress their private information in favour of the market consensus, the authors argue that herding behaviour is revealed when the dispersion of individual equity returns cluster around the market return. Therefore, to empirically test for herding in the US stock market they measured the cross-sectional standard deviation (CSSD) of equity returns under extreme market conditions and found that herding was not present in the US market.

However, according to Chang et al. (2000), the model was incorrectly specified as it failed to account for the non-linear relationship between equity return dispersion and market returns during periods of market herding. To account for this relationship Chang et al. (2000), developed the cross-sectional absolute deviation of returns (CSAD) model. They assessed the directional asymmetry documented by McQueen et al. (1996) on herding behaviour. By analysing the daily equity returns of five different stock markets, the researchers were only able to detect herding in the Taiwan and South Korea markets (emerging markets) but not in

[2] Christie and Huang (1995) notes that the definition of market stress is arbitrary. They therefore define it as market returns that lie at the upper or lower tails of the market return distribution.

the Japanese, US and Hong Kong markets (developed markets). Moreover, their results reveal that herding is present in both up and down market periods for the two emerging markets.

When analysing herding at the aggregate level the two aforementioned papers have formed the bedrock for empirical analysis in the herding literature. This has seen herding being tested in both developed and emerging markets, under different methodologies and during various time periods in order to better explain the phenomena.

By analysing the Chinese stock market Damirer and Kutan (2006), finds no evidence of herding in both the aggregate and sectoral level. However, it should be noted that the study utilised the CSSD model which has been shown to be ineffective in detecting herding. Tan et al. (2008), extended the work of Damirer and Kutan (2006), by investigating herding behaviour in the Chinese market by separately analysing the two types of shares traded on the Shanghai and Shenzhen stock exchange. The reason for this distinction is to capture the different investor behaviours as type A-shares can only be traded by domestic investors, while type B-shares are traded by both foreign and domestic investors. By using the CSAD model they were able to find evidence of herding within both stock exchanges and share classes. However, asymmetric herding behaviour was only found in the Shanghai A-shares during rising markets.

These findings contradict those of Yao et al. (2014), who finds herding to be present only in type B-shares and not in type A-shares. The authors suggest that the herding found in type A-shares by Tan et al. (2008) might be spurious as the authors fail to incorporate lagged values of the dependent variable to account for the autocorrelation in the data. Furthermore, investors in both Shanghai and Shenzhen markets herd more in down markets than in up markets, which stands in contrast to the findings of Tan et al. (2008).

By analysing a broad range of developed European countries[3] Mobarek et al. (2014), finds insignificant herding results for the entire period: 2001-2012. Given the behavioural tendencies of investors to herd during periods of market panic, the authors augmented the benchmark model and found significant herding coefficients during the great financial crisis. Moreover, they found the herding coefficient to be statistically significant during days of negative returns

[3] The study considers the following countries: Portugal, Italy, Ireland, Greece, Spain, Finland, Norway, Sweden, Denmark, France and Germany.

only for Portugal, Greece, Finland and Sweden. In a comparative study of 18 countries from both developed and emerging markets Chiang and Zheng (2010), finds significant evidence in support of herding in all countries besides the US and Latin American countries. Furthermore, they find herding to be more pronounced during the Asian crisis, Mexican crisis and financial crisis.

Although the above papers test for herding towards the market return under different market conditions they however, do not directly test for the sensitivity of herding estimates towards investor fear. This is an important aspect to analyse as it is an implicit assumption that underlies most of the herding estimates during periods of market stress. In order to test for the impact of fear on herding estimations Philippas et al. (2013), incorporated the VIX in their CSAD model to proxy US investor fear when analysing the US REITs market. This is due to the VIX being widely acknowledged as the US investor "fear gauge" because when investors are anxious/fearful about future market performance, they tend to follow insurance like strategies, which drives up the value of the index (Whaley, 2009).

When analysing the REITs market Philippas et al. (2013), finds no evidence of herding towards the market return but investors were found to herd during bear markets. However, the dispersion of REITs cross sectional returns increased during the financial crisis, which is counterintuitive given that herding was found to be present during down market periods. When incorporating the VIX index, the authors find significant evidence of herding towards the fear index. This suggests that when investors become fearful they tend to ignore their personal information and instead follow the market consensus.

By analysing herding in the US, German and UK markets Economou et al. (2018), finds no evidence of herding towards the market index which is in line with the results of Chang et al. (2000) and Philippas et al. (2013). By using the domestic fear indices of each country the authors find that investors herd towards their respective fear indices. Due to the interconnectedness of financial markets Economou et al. (2018), goes a step further by testing for cross market herding between each country. Although investor fear in the UK market has no impact on herding behaviour in the US, increases in the VIX does however influence herding estimates in the German and UK stock markets. The significance of US investor fear on cross country herding has also been documented in frontier markets such as Taiwan and Romania (Huang & Wang, 2017; Economou, 2019).

Although herding has garnered a lot of attention abroad, the empirical studies in South Africa have remain limited. Using monthly data over the period 1999 to 2011, Seetharam and Britten (2013) finds no evidence of herding in the overall market, except during bear markets. The overall result is not surprising, as monthly data generates significantly higher levels of dispersion compared to daily frequencies – giving individual returns more time to deviate from the mean (Christie & Huang, 1995).

In a more recent study, Ababio and Mwamba (2017) uses a quantile regression approach to analyse herding behaviour in the financial industry over the period: January 2010 to September 2015. This paper focuses on a sub-sector of the JSE namely the financial sector, which comprises of banking, general financials, insurance and real-estate. Out of the four sub-sectors analysed, herding was found to be present in only the banking and real estate sectors. However, in the entire financial industry herding behaviour was only found in extreme up market periods (90^{th} quantile). Although this paper examines the financial industry it does not incorporate the global financial crisis in its analysis, this is surprising given the significance of that period for the global financial sector. A further drawback of this study is that it does not show the extent to which herding within the sector coincides with herding in the overall market. It therefore does not shed light on the broader herding behaviour in South Africa.

By analysing the top 100 stocks on the JSE by market capitalisation, using an Autoregressive Distributed Lag (ARDL) model, Niyitegeka and Tewari (2015) finds herding to be present in bull markets and not bear markets. Despite having a sample that spans from August 2006 to August 2011, the authors fail to isolate the 2007/8 global financial crisis in their analysis, notwithstanding the ARDL model indicating that herding is a short-lived phenomenon. Moreover, this paper does not investigate any spill-over effects from developed markets to explain herding in emerging markets (e.g. South Africa), which is an area of research that is highlighted by Chiang and Zheng (2010). A sample of the top 100 stocks is relatively small when testing for herding in the overall market, as smaller market capitalisation stocks will be underrepresented.

Furthermore, the South African literature does not mention any attempts to account for survivorship bias within their datasets. This bias occurs when your dataset only consists of currently listed companies, and not the set of companies that existed over the period being analysed (Economou, 2019). Not controlling for this bias could distort herding estimates and lead to overly optimistic results in favour of herding (Seetharam & Britten, 2013). This may come about as investors are less inclined to herd towards stocks that are likely to become delisted and instead flock towards those that are performing relatively well and are more likely to remain in the index.

Moreover, the models used in the above two papers (ARDL and quantile regression models) are used for unique purposes, the ARDL model is used to establish the speed at which herding adjust to its long run level, while the quantile regression is used to define extreme market periods. Given that this paper isolates the 2007/8 financial crisis as an extreme market period and investigates how domestic and international fear affects herding behaviour in South Africa, the CSAD model by Chang et al. (2000), augmented with the fear indices (SAVI and VIX), provides an intuitive way to capture this phenomena, as the cross sectional dispersion of individual asset returns decrease when herding is present.

Overall, there is mixed evidence for the detection of herding towards the market return in both international and domestic stock markets. The recent literature has shown that explicitly accounting for investor fear in herding models can provide further insights into investor behaviour during periods of market stress. This is important for regulators when implementing policies during periods of heightened investor fear, and for investors to position their portfolios to take advantage of market inefficiencies. Therefore, the well-developed capital markets in South Africa lends itself well for the analysis of investor fear on market herding from an emerging market perspective.

3. Data and Methodology

3.1. Data

The dataset used in this paper contains daily closing prices of the constituents of the JSE All Share Index (ALSI), including data on stocks that have left the index or became inactive/delisted over the sample period: 2 May 2002 to 31 December 2019. This brings the total amount of unique stocks in the overall sample to 357. The closing index price of the ALSI was collected over the same time period and is used as the proxy for the market.

Since the SAVI was only launched in 2007, data was collected from 1 February 2007 to 31 December 2019. However, daily closing data on the VIX was collected from 2 May 2002 to 31 December 2019. All the data was extracted from Thompson Reuters (Refinitiv Eikon) Datastream and Bloomberg L.P.

It has been shown that herding becomes more intense during periods of market crises but then dissipates over time (Philippas et al., 2013; Economou et al., 2018). Therefore, the great financial crisis of 2007/8 provides a framework to test this hypothesis. Furthermore, the sample period after the crisis is sub-divided to account for endogenous structural breaks after the crisis so as to investigate whether herding around the fear indices dissipates over time.

3.1. Methodology

A common measure of herding is the cross-sectional standard deviation (CSSD) of returns proposed by Christie and Huang (1995). However, the model suffers from two drawbacks. The first being that the CSSD is susceptible to outliers (Economou et al., 2011). Secondly, it does not account for the non-linear relationship between return dispersion and market return. Therefore, this paper uses Chang et al.'s (2000) alternative model, which measures the cross-sectional absolute deviation (CSAD) of stock returns around the market return.

The CSAD is the average of the aggregate difference between the expected return of the individual stocks and the market return, and is given by:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} | R_{i,t} - R_{m,t} | \quad (1)$$

Where $R_{i,t}$ is the observed stock return for firm i on day t,
N is the number of stocks on day t, and
$R_{m,t}$ is the return on the ALSI which serves as the market return.

The ALSI represents 99% of the market capitalisation of the JSE (Russell, 2017). Stock returns and market returns are calculated as $\mathrm{R_{i,t}} = 100 \times (\ln(\mathrm{P_{i,t}}) - \ln(\mathrm{P_{i,t-1}}))$, resulting in a sample of 4413 daily observations. To assess herding, this study uses the seminal approach by Chang et al. (2000) specified as follows:

$$\mathrm{CSAD_t} = \alpha + \theta_1 |\mathrm{R_{m,t}}| + \theta_2 \mathrm{R_{m,t}^2} + \varepsilon_t \quad (2)$$

where α is the intercept, θ_1 is the coefficient of the absolute value of the market return ($|\mathrm{R_{m,t}}|$), θ_2 is the coefficient of the square of the market return ($\mathrm{R_{m,t}^2}$) and ε is the error term.

The above specification is based on the predictions of rational asset pricing models, which states that each security differs in their reaction to the market return, so as to reflect the different believes held by investors (Tan et al., 2008). Therefore, in the absence of herding behaviour a positive and linear relationship should exist between the dispersions of individual asset returns and the returns in the market portfolio.

Chang et al. (2000) argues that this relationship becomes negative and non-linear when herding is present, which is captured by the inclusion of the $\mathrm{R_{m,t}^2}$ term. This is intuitively appealing, because during periods of market stress investors are predicted to act homogenously, causing asset returns to become highly correlated. This results in the deviation of individual asset returns from the market return to increase at a decreasing rate as investors conform to the market consensus. If θ_2 is negative and statistically significant it means investors are herding towards the market portfolio. It is important to note, that the absence of herding as measured by this equation should not be construed as implying that other forms of herding does not exist (Yao et al., 2014).

Although equation 2 is theoretically sound, it does not correct for the multicollinearity between $|\mathrm{R_{m,t}}|$ and $\mathrm{R_{m,t}^2}$, which can lead to insignificant results in general. Furthermore, due to the nature of time series data serial correlation was found to be present in the data, which if left unresolved can lead to biased coefficients. To resolve the aforementioned issues Yao et al. (2014) recommends modifying the original equation as follows:

$$\mathrm{CSAD_t} = \alpha + \theta_1 |\mathrm{R_{m,t}}| + \theta_2 (\mathrm{R_{m,t}} - \overline{\mathrm{R}}_{\mathrm{m,t}})^2 + \theta_3 \mathrm{CSAD_{t-1}} + \varepsilon_t \quad (3)$$

where θ_2 is the coefficient of the demeaned market return and θ_3 is the coefficient of the 1-day lag of the dependent variable.

To overcome the problem of multicollinearity the arithmetic mean ($\overline{R}_{m,t}$) is subtracted from the market return ($R_{m,t}$). To address the problem of serial correlation and heteroscedastic errors, the Newey and Western (1986) heteroscedasticity and autocorrelation consistent standard errors were used to calculate the regression coefficients. Furthermore, the one-day lag of the dependant variable ($CSAD_{t-1}$) is also included, so as to eliminate any spurious relationships caused by autocorrelation. This paper will thus make use of equation 3 to test for the overall presence of herding in the JSE, the θ_1 and θ_2 coefficients have the same interpretation as in equation 2 but are more econometrically sound.

Since the direction of the market return may affect investor behaviour, equation 4 and 5 tests for herding behaviour in both up and down market returns. The system can be written as:

$$CSAD_t^{UP} = \alpha + \theta_1^{UP}|R_{m,t}^{UP}| + \theta_2^{UP}(R_{m,t}^{UP} - \bar{R}_{m,t}^{UP})^2 + \theta_3^{UP}CSAD_{t-1}^{UP} + \varepsilon_t, if\ R_{m,t} > 0 \quad (4)$$

$$CSAD_t^{DOWN} = \alpha + \theta_1^{DOWN}|R_{m,t}^{DOWN}| + \theta_2^{DOWN}(R_{m,t}^{DOWN} - \bar{R}_{m,t}^{DOWN})^2 + \theta_3^{DOWN}CSAD_{t-1}^{DOWN} + \varepsilon_t, if\ R_{m,t} < 0 \quad (5)$$

Where $R_{m,t}^{UP}$ is the market return at time t when the market rises and $(R_{m,t}^{UP} - \bar{R}_{m,t}^{UP})^2$ is the square of the demeaned market return during up market periods. $CSAD_t^{UP}$ is the $CSAD_t$ at time t which corresponds to $R_{m,t}^{UP}$ and $CSAD_{t-1}^{UP}$ is the one period lag of $CSAD_t^{UP}$. Similarly, the variables with the superscript “down” refer to periods in which the market is declining.

Since herding is more pronounced during periods of market uncertainty and fear, equation 3 is augmented by the inclusion of the SAVI in order to test the impact of investor fear on herding.

$$CSAD_t = \alpha + \theta_1|R_{m,t}| + \theta_2(R_{m,t} - \overline{R}_{m,t})^2 + \theta_3 SAVI_t + \theta_4 CSAD_{t-1} + \varepsilon_t \quad (6)$$

Where the $SAVI_t$ represents the percentage daily change in the South African Volatility Index. According to Economou et al. (2018), a negative and statistically significant θ_3 coefficient indicates that herding increases during periods of increased uncertainty and fear. Although the SAVI measures the domestic market's expectations of the 3-month volatility of the FTSE/JSE Top 40 index, it has been shown to be a reliable measure of fear within the overall market (Kotzé et al., 2009).

Finally, since the US plays a significant role in international financial markets, equation 7 takes into account the spill-over effects of US investor fear on the South African equity market. The one-day lag of the VIX variable is used to account for the time difference between the South African and US stock markets, which reduces the possibility of a contemporaneous relationship to exist (Economou et al., 2011). Therefore, VIX_{t-1} represents the one-day lagged percentage daily change of the VIX.

$$\mathrm{CSAD}_t = \alpha + \theta_1|\mathrm{R}_{m,t}| + \theta_2(\mathrm{R}_{m,t} - \overline{\mathrm{R}}_{m,t})^2 + \theta_3\mathrm{VIX}_{t-1} + \theta_4\mathrm{CSAD}_{t-1} + \varepsilon_t \quad (7)$$

3.3. Descriptive Statistics

Table 1 reports the descriptive statistics for the daily cross-sectional absolute deviations (CSAD), market return (R_m), and daily percentage change in the CBOE Implied Volatility Index (VIX) over the period: 3 May 2002 to 31 December 2019. Since the South African Volatility Index (SAVI) was only officially launched in 2007 the data sample for this variable only spans from 2 February 2007 to 31 December 2019.

Table 1. Summary Statistics

	Obs.	Mean	Std. dev	Min	Max
CSAD	4413	1.820	0.540	0.820	6.332
R_m	4413	0.037	1.163	-7.581	6.833
SAVI	3225	0.031	2.782	-16.209	19.833
VIX	4413	0.248	7.409	-29.573	115.598

This table reports the mean, standard deviation, minimum values, maximum values of the cross sectional absolute deviation (CSAD_t), market return ($\mathrm{R}_{m,t}$), change in the South African Volatility Index (SAVI_t) and the change in the CBOE Implied Volatility Index (VIX_t). The sample period spans from 3 May 2002 to 31 December 2019 for each variable besides the SAVI, which is available from 2 February 2007 to 31 December 2019.

By definition, when individual stock returns are perfectly correlated with the market, the CSAD will take on a value of zero and will increase as returns deviate from the market. The mean value of the CSAD variable is 1.82%, which is greater than the 1.262% found by Niyitegeka and Tewari (2015) in the South African market. One possible reason for the lower CSAD value by Niyitegeka and Tewari (2015) is their smaller sample size (August 2006 to August 2011). Furthermore, the average market return ($\mathrm{R_m}$) is positive, indicating a positive market performance over the period: May 2002 to December 2019.

Both the SAVI and the VIX have positive mean values, indicating that the average market sentiment was negative over the period February 2007-December 2019 and May 2002-December 2019, respectively. This is because when there is increased fear and uncertainty in the market the fear gauges increase, but decreases when market sentiment becomes more positive. The standard deviation of the VIX is greater than the SAVI, suggesting that US sentiment is a lot more volatile.

4. Empirical Results

Table 2 reports the regression results of the augmented CSAD model as stylised by Yao et al. (2014), using Newey and West (1986) consistent estimators. The coefficient on the lagged variable $\mathrm{CSAD_{t-1}}$ is large and statistically significant, which suggests that the dispersion variable ($\mathrm{CSAD_t}$) is strongly correlated with its previous values. Therefore, Newey and West (1986) standard errors method is used in each model to overcome any issues of serial correlation and heteroscedasticity in the error terms.

The "Overall" column is analysed first, which tests for herding across the entire sample period: 3 May 2002 to 31 December 2019. The herding coefficient (θ_2) is positive and statistically significant, which provides evidence against the hypothesis that herding, as measured by market returns, is present in the South African market.

Herding is theorised to be more pronounced during extreme market periods, therefore table 2, column 3, provides results to test whether herding was present during the financial crisis. Column 3 defines the crisis period from the 10th of October 2007, when the Dow Jones Industrial Average (DJIA) started to decline, to the 6th of March 2009, when the index reached its lowest point before recovering. Column 2 represents the pre-crisis period from 3 May 2002 to 9 October 2007, while column 4 captures the post-crisis period, measured from 7 March 2009 to 31 December 2019.

The coefficients on the squared market return variable ($(R_{m,t} - \overline{R}_{m,t})^2$) are positive and statistically significant for all time periods besides the pre-crisis period. These results corroborate the findings by Seetharam and Britten (2013) and Chiang and Zheng (2010) for South Africa and Latin America, respectively. Furthermore, table 3 reveals no evidence of herding in down market periods, which is in line with the domestic literature (Niyitegeka & Tewari, 2015; Ababio & Mwamba, 2017). This is counterintuitive, as one would expect investors in emerging markets to herd during periods of decreasing returns. The absence of herding towards the market return variable in developed countries have been argued to indicate that those markets are efficient. However, this argument is less plausible when applied to emerging/developing markets which have been shown to have less developed financial markets and greater informational asymmetries (Kallinterakis & Kratunova, 2007).

It is important to note that the occurrence of "negative herding", i.e. a positive coefficient on θ_2, is not an anomaly, but instead a common occurrence in certain countries. This means that the results in table 2 and 3 suggest that market participants do not use large price movements as a signal to suppress their views in order to follow the market consensus. In light of this behaviour, Gębka and Wohar (2013) suggests that under extreme market conditions investor fear will encourage a "flight to quality" phenomena. Which refers to the excessive selling of risky assets during highly volatile market periods, as investors rebalance their portfolios towards more safer assets. These types of large capital flows from risky to safe assets would result in cross sectional dispersion of returns to increase above their rational levels. This is particularly relevant for emerging markets such as South Africa, as investors seek safer assets abroad during extreme market conditions.

Although the above table provides evidence in favour of "negative herding" in the South African market, it is important to note that there are studies, such as Lao and Singh (2011) and Chen (2013), who find evidence in favour of herding within developed and emerging markets. This may suggest that the squared market return ($(R_{m,t} - \overline{R}_{m,t})^2$) variable fails to capture investor fear during volatile market periods.

Therefore, in order to better understand the herding phenomena in South African, table 4 reports the results of the CSAD model augmented with the fear indicator (SAVI). Column 1 tests for herding across the entire sample period for which the SAVI was available: 2 February 2007 to 31 December 2019. Although there is no evidence of herding towards the market return, there is strong evidence of herding towards the fear indicator. This is shown by the negative and statistically significant θ_3 coefficient. Therefore, when investors are fearful, it causes them to follow the market consensus, as shown by the decrease in the dispersion of individual stock returns from the market return (CSAD). This is in line with the findings of Economou et al. (2018), as these authors also fail to detect herding towards the market return with the traditional CSAD model but found strong evidence of herding towards the domestic fear indices within the US, UK and German markets.

Table 2. Regression results of the modified CSAD model.

Variables	(1) Overall	(2) Pre-crisis	(3) Crisis	(4) Post-crisis
α	0.796*** (24.872)	0.977*** (17.818)	0.935*** (10.508)	0.730*** (15.242)
$\lvert R_{m,t} \rvert$	0.240*** (13.437)	0.326*** (8.906)	0.283*** (7.138)	0.149*** (7.076)
$(R_{m,t} - \overline{R}_{m,t})^2$	0.033*** (5.790)	0.012 (1.030)	0.025*** (3.019)	0.055*** (7.486)
$CSAD_{t-1}$	0.426*** (23.583)	0.310*** (9.713)	0.390*** (10.229)	0.480*** (17.532)
Adjusted R^2	0.586	0.407	0.772	0.504
N	4412	1358	353	2701

This table presents the estimated coefficients of the benchmark model: $CSAD_t = \alpha + \theta_1 \lvert R_{m,t} \rvert + \theta_2 (R_{m,t} - \overline{R}_{m,t})^2 + \theta_3 CSAD_{t-1} + \varepsilon_t$ i.e. equation 3. Where $CSAD_t$ is the cross-sectional absolute deviation of returns, $\lvert R_{m,t} \rvert$ and $(R_{m,t} - \overline{R}_{m,t})^2$ denote the absolute return and de-meaned squared return of the JSE All Share Index, respectively. While α and $CSAD_{t-1}$ represent the constant term and the one-day lag of the $CSAD_t$, respectively. N refers to the number of observations. Columns 1 to 4 represent the different sub-periods of analysis. Where column 1 is from: 3 May 2002 to 31 December 2019, column 2 is from: 3 May 2002 to 9 October 2007, column 3 is from: 10 October 2007 to 6 March 2009, and column 4 is from: 7 March 2009 to 31 December 2019. The t-statistics are in parenthesis. ***, ** and * represent statistical significance at the 1%, 5% and 10 % level respectively.

Table 3. Regression results of rising and declining market returns.

VARIABLES	Up Market	VARIABLES	Down Market
α	0.802***	α	0.794***
	(18.552)		(20.317)
$\vert R_{m,t}^{UP}\vert$	0.262***	$\vert R_{m,t}^{DOWN}\vert$	0.210***
	(9.773)		(8.710)
$(R_{m,t}^{UP}-\bar{R}_{m,t}^{UP})^2$	0.036***	$(R_{m,t}^{DOWN}-\bar{R}_{m,t}^{DOWN})^2$	0.033***
	(3.869)		(5.005)
$CSAD_{t-1}^{UP}$	0.417***	$CSAD_{t-1}^{DOWN}$	0.434***
	(17.424)		(19.168)
Adjusted R^2	0.588	Adjusted R^2	0.587
N	2333	N	2078

This table presents the estimated coefficients of the benchmark model during up and down periods of the market: $CSAD_t^{UP}=\alpha+\theta_1^{UP}|R_{m,t}^{UP}|+\theta_2^{UP}(R_{m,t}^{UP}-\bar{R}_{m,t}^{UP})^2+\theta_3^{UP}CSAD_{t-1}^{UP}+\varepsilon_t, if\ R_{m,t}>0$; $CSAD_t^{DOWN}=\alpha+\theta_1^{DOWN}|R_{m,t}^{DOWN}|+\theta_2^{DOWN}(R_{m,t}^{DOWN}-\bar{R}_{m,t}^{DOWN})^2+\theta_3^{DOWN}CSAD_{t-1}^{DOWN}+\varepsilon_t, if\ R_{m,t}<0$. The sample period is from 3 May 2002 to 31 December 2019. The t-statistics are in parenthesis. ***, ** and * represent statistical significance at the 1%, 5% and 10 % level respectively.

This paper also tests whether herding towards the fear index becomes more pronounced during the global financial crisis. Table 4, column 3, re-estimates the regression in column 1, but only for the period 10 October 2007 to 6 March 2009 i.e. financial crisis period. It is clear from table 4 that herding towards the domestic fear index increases during the financial crisis, as the coefficient on the SAVI increases from -0.006 to -0.030 while being statistically significant at the 1% level. This together with a positive and statistically significant θ_2 coefficient during the crisis period, highlights the “flight to quality” argument when investors are fearful.

In order to better understand the relationship between return dispersion and fear, table 4 separates the data into pre and post-crisis periods (columns 2, 4 and 5). Due to data limitations the pre-crisis period is only from the 2nd of February 2007 to the 9th of October 2007. Since the detection of herding is sensitive to the time period under analysis a Quandt-Andrews breakpoint test was performed on equation 6 in order to detect any structural breaks in the data after the financial crises. The model suggests the existence of a structural break on the 7th of November 2017. Instead of using a dummy variable to account for the break in the data, this paper will follow the work of Philippas et al. (2013) and Economou et al. (2018) by dividing the data into two sub-periods: 7th March 2009-8th November 2017 (first sub-period post crisis) and 9th November 2017-31st December 2019 (second sub-period post crisis).

Table 4, column 2, reveals that herding towards the fear index was present in the pre-crisis period. It is interesting that herding was present in the pre-crisis period, because tranquil environments are usually not associated with investor panic. Although this finding is counter-intuitive, it should be noted that due to data limitations the pre-crisis period consists of 171 observations prior to the crisis.

Furthermore, it appears that fear also affects herding in the first sub-period after the crisis as the θ_3 coefficient is negative and statistically significant at the 10% level. As expected, the impact of fear is less pronounced during the post-crisis phase as the coefficient decreases from -0.030 to -0.004. Moreover, herding is absent in the second sub-period as θ_3 becomes positive and statistically insignificant. The absence of herding in the second sub-period is similar to the findings by Philippas et al. (2013) and Economou et al. (2018), who shows that herding is present after a crisis but dissipates over time.

Furthermore, South Africa does not operate in isolation and is a popular destination for foreign investors among emerging markets. This is highlighted by the JSE's market capitalization being around a 190% greater than the country's gross domestic product (GDP) and it has consistently been in the top twenty largest stock markets in the world (Hassan, 2013). Furthermore, research by Mensi et al. (2016) has shown the South African stock market to be correlated with the US. Therefore, it is important to measure how herding on the JSE is affected by fear in the US, which is measured by the VIX. Table 5 reports the empirical results of equation 7, which is the CSAD model augmented with a one-day lag VIX variable (VIX_{t-1}). The coefficient on the VIX variable in columns 1 and 2 are negative and statistically significant at the 5% and 10% level, respectively. The result in column 1 suggests that herding in the South African market is in part affected by fear in international markets over the sample period: 3 May 2002 to 31 December 2019. In a study by Economou et al. (2018), the VIX had a similar effect on herding in the German stock exchange from January 2004 to July 2014.

However, during the financial crisis the coefficient on the VIX remains negative but not statistically significant. This would suggest that, on average, the prevailing fear in the US market during the financial crisis did not spill-over into the South African market, as individual asset returns on the JSE did not cluster around the market return. The absence of herding over the defined crisis period does not necessarily imply that fear abroad had no impact domestically.

Thus, to account for any short-term herding behaviour during the financial crisis Philippas et al. (2013), suggests using a more narrow definition of the crisis. Despite the sample only having 44 observations, the reason for using this as an alternative definition for the crisis period is that it coincides with the bankruptcy of Lehman Brothers[4], which is identified as a critical turning point within the financial markets (Johnson & Mamun, 2012). This narrow definition of the crisis is captured in table 5, column 4, and the θ_3 coefficient is negative and statistically significant at the 5% level. During this short period the coefficient on the squared market return variable also becomes negative but is not statistically significant. This confirms the expectations that the panic caused by the Lehman Brothers' bankruptcy had implications for herding in the South African market.

To gain further insights into the impact of the VIX, a Quandt-Andrews breakpoint test was performed on equation 7 over the post crisis period, and a structural break was found on the 7th of November 2017. Table 5 separates the data into two sub-periods: 7th March 2009-8th November 2017 (first sub-period, post-crisis) and 9th November 2017-31st December 2019 (second sub-period, post-crisis). Table 5 shows that after the crisis the VIX variable remains negative and statistically insignificant.

[4] The bankruptcy of the fourth largest US investment bank signifies the intensity of the financial crisis as it was the largest bankruptcy in US history.

Table 4. Regression results of the modified CSAD model augmented with the SAVI.

Variables	(1) Overall	(2) Pre-crisis	(3) Crisis	(4) 1st Sub-period Post-crisis	(5) 2nd Sub-period Post-crisis
α	0.740***	1.307***	0.946***	0.803***	1.450***
	(19.086)	(14.195)	(10.596)	(13.615)	(13.950)
$\lvert R_{m,t} \rvert$	0.210***	0.312***	0.295***	0.184***	0.050
	(11.112)	(3.530)	(7.268)	(8.676)	(0.963)
$(R_{m,t} - \overline{R}_{m,t})^2$	0.038***	0.001	0.025***	0.053***	0.079***
	(6.278)	(0.045)	(3.190)	(7.068)	(4.070)
$SAVI_t$	-0.006***	-0.016**	-0.030***	-0.004*	0.0002
	(-2.880)	(-2.022)	(-4.163)	(-1.679)	(0.047)
$CSAD_{t-1}$	0.460***	0.013	0.379***	0.392***	0.251***
	(20.583)	(0.224)	(9.830)	(10.876)	(4.850)
Adj R^2	0.639	0.296	0.781	0.531	0.236
N	3225	171	353	2166	535

This table presents the estimated coefficients of the augmented CSAD model using the SAVI as the fear factor: $CSAD_t = \alpha + \theta_1 \lvert R_{m,t} \rvert + \theta_2 (R_{m,t} - \overline{R}_{m,t})^2 + \theta_3 SAVI_t + \theta_4 CSAD_{t-1} + \varepsilon_t$ i.e. equation 6. Where $CSAD_t$ is the cross-sectional absolute deviation of returns, $\lvert R_{m,t} \rvert$ and $(R_{m,t} - \overline{R}_{m,t})^2$ denote the absolute return and de-meaned squared return of the JSE All Share Index, respectively. While α and $CSAD_{t-1}$ represent the constant term and the one-day lag of the $CSAD_t$, respectively. N refers to the number of observations. The $SAVI_t$ represents the South African Volatility Index, which measures the expected 3-month volatility of the FTSE/JSE top 40 index. Columns 1 to 5 represent the different sub-periods of analysis. Where column 1 is from: 2 February 2007 to 31 December 2019, column 2 is from: 2 February 2007 to 9 October 2007, column 3 is from: 10 October 2007 to 6 March 2009, column 4 is from: 7 March 2009 to 8 November 2017 and column 5 is from 9 November 2017 to 31 December 2019.The t-statistics are in parenthesis. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively.

Table 5. Regression results of the modified CSAD model augmented with the VIX.

Variables	(1) Overall	(2) Pre-crisis	(3) Crisis	(4) Lehman Brothers' Bankruptcy	(5) 1st Sub-period Post-crisis	(6) 2nd Sub-period Post-crisis
α	0.794***	0.977***	0.931***	0.610*	0.801***	1.448***
	(24.888)	(17.865)	(10.435)	(1.889)	(13.658)	(14.761)
$\lvert R_{m,t} \rvert$	0.241***	0.327***	0.285***	0.547***	0.184***	0.053
	(13.462)	(8.851)	(7.094)	(3.881)	(8.789)	(0.977)
$(R_{m,t} - \overline{R}_{m,t})^2$	0.033***	0.012	0.024***	-0.081	0.053***	0.078***
	(5.750)	(1.065)	(2.875)	(-1.670)	(7.101)	(3.952)
VIX_{t-1}	-0.002**	-0.003*	-0.003	-0.015**	-0.001	-0.001
	(-2.154)	(-1.938)	(-1.280)	(-2.040)	(-0.899)	(-0.776)
$CSAD_{t-1}$	0.427***	0.311***	0.392***	0.422**	0.394***	0.252***
	(23.649)	(9.753)	(10.201)	(2.390)	(10.999)	(5.107)
Adj R^2	0.586	0.408	0.772	0.293	0.530	0.237
N	4412	1358	353	44	2166	535

This table presents the estimated coefficients of the augmented CSAD model using the VIX as an international fear factor: $CSAD_t = \alpha + \theta_1 \lvert R_{m,t} \rvert + \theta_2 (R_{m,t} - \overline{R}_{m,t})^2 + \theta_3 VIX_{t-1} + \theta_4 CSAD_{t-1} + \varepsilon_t$ i.e. equation 7. Where $CSAD_t$ is the cross-sectional absolute deviation of returns, $\lvert R_{m,t} \rvert$ and $(R_{m,t} - \overline{R}_{m,t})^2$ denote the absolute return and de-meaned squared return of the JSE All Share Index, respectively. While α and $CSAD_{t-1}$ represent the constant term and the one-day lag of the $CSAD_t$, respectively. N refers to the number of observations. The VIX_{t-1} represents the CBOE Volatility Index, which measures the expected 30-day volatility of the S&P 500 options. Columns 1 to 6 represent the different sub-periods of analysis. Where column 1 is from: 3 May 2002 to 31 December 2019, column 2 is from: 3 May 2002 to 9 October 2007, column 3 is from: 10 October 2007 to 6 March 2009, column 4 is from: 31 August 2007 to 1 November 2007, column 5 is from 7 March 2009 to 8 November 2017 and column 6 is from 9 November 2017 to 31 December 2019. The t-statistics are in parenthesis. ***, ** and * represent statistical significance at the 1%, 5% and 10% level respectively

5. Conclusion

This paper provides new evidence on the relationship between herding behavior and fear, which has been neglected in the emerging markets literature. By initially using the benchmark CSAD model to examine herding towards the market consensus during periods of market stress, this paper suggests evidence of anti-herding behavior in South African over the period under study. This is in line with emerging market expectations as investors tend to reduce their exposure of riskier assets during periods of market stress. This is contrary to the domestic literature by Niyitegeka and Tewari (2015), who found herding on the JSE despite it being a very short phenomena. However, these results support the findings of Ababio and Mwamba (2017) who found no herding in the financial industry when considering the entire return distribution (herding was only found above the 90% threshold).

In order to capture the impact of fear on herding, the CSAD model was augmented with the SAVI, which revealed that market participants on the JSE herd towards the domestic fear gauge and not the market return. Furthermore, herding towards the fear index was shown to be dynamic as it was present before, during and after the financial crisis but then subsequently dissipated. Herding towards the fear index during a crisis supports the conjecture by Keynes (1936), that investors act irrationally when they are fearful.

Finally, the empirical results indicate that there is a weak link between the VIX in the U.S. and herding in the JSE. However, the fear that was generated during the bankruptcy of Lehman Brothers appears to have a spill-over effect on the JSE as individual asset returns seem to cluster around the market return, although the sample size of 44 observations is relatively small. This study provides insights into the JSE for investors and regulators in that during periods of market fear investors tend to reduce their exposure of riskier assets towards more safer ones. Therefore, regulators should engage with financial institutions (e.g. banks and the asset management industry) during periods of market stress in order to assess the causes of market panic and implement policies to curtail market uncertainty.

It would be interesting to examine herding under different market conditions, while differentiating between large and small stocks, as larger stocks are more liquid and would thus react differently compared to smaller stocks. Although this study looked at spillover effects, future research could investigate the extent to which foreign investors affect herding on the JSE. These suggestions were not conducted in this research due to data limitations.

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