HERDING BEHAVIOUR DYNAMICS IN THE NAMIBIAN SECURITIES EXCHANGE

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Abstract

The main purpose of this research was to analyse herding behaviour dynamics in the Namibian Securities Exchange (NSX) for the period 1st January 2003 to 30th June 2023 using weekly and monthly data series. The time-varying transition probability Markov two-Regime Switching model (MRSM) was used to estimate the equations which is able to capture time-varying phenomenon of herding behaviour. This study employed the cross-sectional absolute standard deviation (CSAD) proposed by Chang, Cheng and Khorana (2000) as the proxy for herding behaviour. The first paper examined the existence of herding behaviour in the NSX as a whole. The static results revealed absence of herding behaviour for the period under review. However, herding behaviour was detected in high volatile regimes after utilising the MRSM which is in line with theory and other previous studies. Thus, management of firms listed on the NSX should improve the flow of information and transparency in terms of disclosure of published financial statements inorder to induce investors' confidence and reduce herding behaviour.

The second paper examined the existence of sectoral herding behaviour in the NSX. The results of the MRSM revealed evidence of herding behaviour for the Industrial and Resource sectors, especially during high volatility regimes. In this regard, it is better to come up with a larger investment portfolio in order to reach the same diversification goal in more volatile state. The third paper examines the influence of variations in South African interest rates and exchange rates on herding behaviour in the NSX. The MRSM produces mixed results regarding the influence of interest rates and exchange rate variations on herding behaviour in the NSX. Herding behaviour is found when all equity stocks are considered, as well as for the sectors save for the Services sector. Results of the changes in interest rates as proxied by the Johannesburg Interbank Average Rate (JIBAR) 3 month yield rate reveal positive (negative) effect on herding behaviour. The exchange rate as proxied by the United States Dollar (USD) to South African Rand (ZAR) is also found to have both positive and negative effect on herding behaviour in the NSX. Furthermore, extreme changes in ZAR appreciation and depreciation also amplified and reduced herding behaviour in the NSX. Thus, coordination and synergy of monetary policies between the Republic of Namibia and Republic of South African (RSA) should be strengthened, since changes in interest rates and exchange rates in South Africa influence herding behaviour in the NSX.

Key words:

Herding Behaviour, Johannesburg Interbank Average Rate (JIBAR), Markov two-Regime Switching model (MRSM), South African Rand (ZAR) Appreciation, and South African Rand (ZAR) Depreciation

Table of contents

List of tables

List of figures

List of Abbreviations and / Acronyms

ADF	Augmented Dick Fuller
AIC	Akaike Information Criterion
BIC	Bayes-Schwartz Information Criterion
CCK	Chang, Cheng and Khorana
CH	Christie and Huang
CSAD	Cross sectional absolute standard deviation
CSSD	Cross sectional standard deviation
DF-GLS	Dickey-Fuller Generalised Least Square
EMH	Efficient market hypothesis
GARCH	Generalised autoregressive conditional heteroscedasticity
HS	Hwang and Salmon
JIBAR	Johannesburg Interbank Average Rate
JSE	Johannesburg Stock Exchange
MRSM	Markov Regime Switching Model
NAD	Namibian dollar
NSX	Namibian Securities Exchange
OLS	Ordinary Least Squares
PP	Philip Perron
Q-Q	Quantile-Quantile
QR	Quantile regression
USD	United States Dollar
ZAR	South African Rand

Dedication

This work is dedicated to God the Almighty for His everlasting blessings bestowed upon me *(Psalms 34 vs 5).* Not forgetting my parents, Eritah Runokunda Mutekwa and Ceiphas Jonas Dembure for being the mainstay of strength in my life.

Acknowledgement

My profound gratitude goes to my supervisors, Prof. E. Ziramba and Dr. J. De Beer for their unwavering support and guidance during the entire course of this research work. Not forgetting my family, relatives, friends and all those who motivated and supported me through this arduous research journey. May God the Almighty bless you all abundantly, exceedingly, above and beyond.

Declarations

I, Honest Dembure, declare hereby that this study is a true reflection of my own research and that this work or part thereof has not been submitted for a degree in any other institution of higher education.

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Chapter 1: Introduction

1.1 Introduction and background of the study

Choi and Skiba (2015) defined herding as a convergence of behaviour whereby investors follow the action of others from security to security and from market to market. Thus, investors disregard their own investment strategies and follow the decisions of a group. Herding can occur due to psychological reasons and the pressure to fit in a group. As argued by Vo and Phan (2017), herding is more prominent in emerging markets where information asymmetry is stronger and Namibia is no exception. Examining herding behaviour is important due to the fact that it leads to stock market instability and mispricing, thereby violating the market efficiency hypothesis. Ababio and Mwamba (2017) and Seetharam and Britten (2013), postulated that there is considerable evidence for the existence of herding behaviour, however, the issue of what drives it and whether it varies across different business sectors, remains unresolved. Most studies have so far produced mixed results which are inconclusive and contradictory. This current study is motivated by a need to fulfill the research gap, which includes dearth of studies on herding behaviour in the Namibian context and use of time-varying transition probability Markov regime-switching model in the study of herding behaviour.

To the researcher's best knowledge, the only published paper done so far on the Namibian context is by Guney *et al*. (2017), which only analysed herding for the whole market, leaving the cross sectoral idiosyncrasies untapped. This current study does not only identify the existence of sectoral herding behaviour, but also examine how macro-economic shocks such as monetary policy changes and exchange rate fluctuations in

South Africa (SA) affect herding behaviour in the Namibian Securities Exchange (NSX). The NSX is greatly affected by movements in other stock markets like the Johannesburg Stock Exchange (JSE) as most equities are dually listed on both the stock exchanges and therefore attracts a lot of investors. Secondly, the paper mentioned above by Guney *et al.* (2017) utilises the OLS which is less superior to the time-varying transition probability Markov regime-switching model utilised in this current study which is able to capture the time varying nature of herding behaviour.

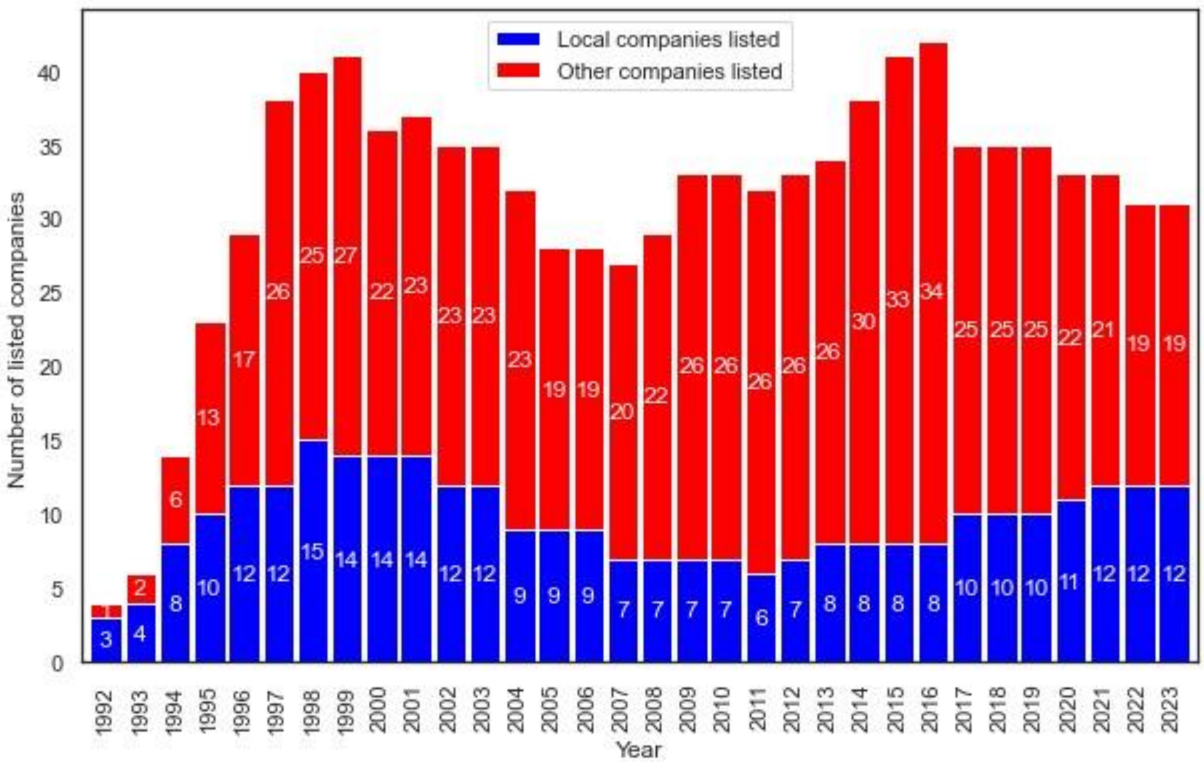
Thirdly, since its inception in 1992, the NSX has witnessed low liquidity due to a number of factors, chief among them, poor corporate governance of firms listed, regulatory constraints and poor quality of information relating to disclosure of financial statements (Matongela & Karodia, 2015). All these variables leads to lack of transparency in the NSX. Bikhchandani *et al*. (1992) averred that lack of transparency is one of the major drivers of herding behaviour. It is against all those mentioned characteristics that a further investigation is required to ascertain the presence and extent of the herding behaviour in the aforementioned equity market and how it is influenced by shocks in the SA macro-economic variables.

1.1.1 Overview of the Namibian Securities Exchange (NSX)

The Namibian Securities Exchange (NSX) was established in 1992. Since its inception in 1992, the NSX has grown in leaps and bounce regarding the number of companies listed as depicted in Figure 1.1 below. The rapid growth in the NSX before the turn of the new millennium can be attributed to the enactment of mandatory regulation by government of

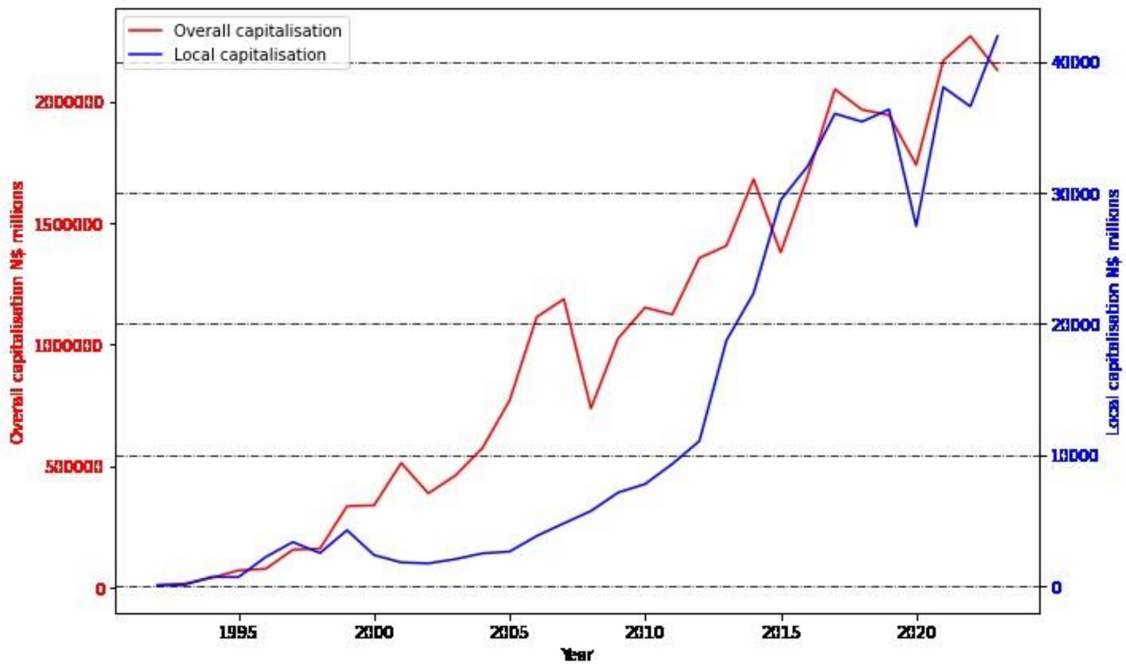
Namibia in 1994, requiring pension and life insurance funds to invest 35% of their assets in Namibian assets encompassing those shares listed on the NSX (Sherbourne & Christoph, 2004). Thus, the acceleration in the development of the NSX and rapid growth in the market capitalisation as depicted in Figure 1.2 before the turn of the new millennium, can be attributed to the introduction of the domestic asset requirements. However, the turn of the new millennium witnessed a down in the growth of the NSX as evidenced by the decline in the number of companies listed on this market. The situation only improved after the 2008-09 Global Financial Crisis as shown in Figure 1.1.

Figure 1.1: Number of listed companies on NSX since its inception in 1992



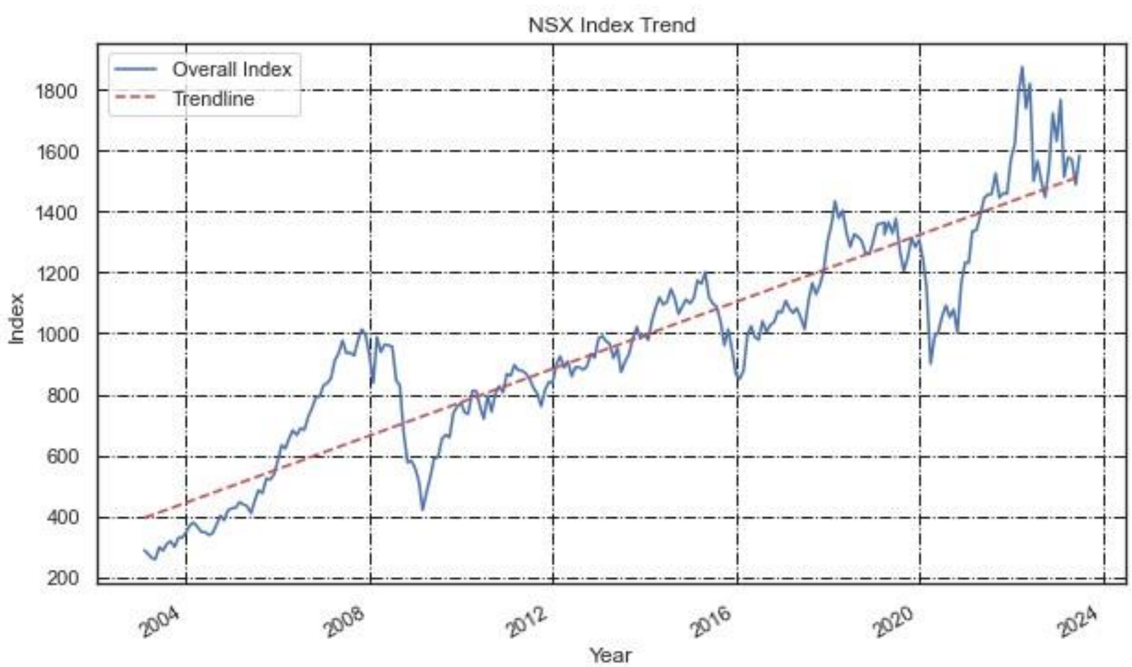
Source: Namibian Securities Exchange (2023)

Figure 1.2: Market capitalisation trend for the NSX since its inception in 1992



Source: Namibian Securities Exchange (2023)

Figure 1.3: Trend in the NSX index for the period 2003-2023



Source: Namibian Securities Exchange (2023)

Figure 1.3 above depicts the trend in the NSX overall index. Figure 1.3 depicts general increase in the overall index from 2003 to 2023. However, the index experienced a dramatic bust, during the 2008-09 global financial crisis, when it dropped by about 57% from 988 in February 2008 to about 420 in February 2009. It also experienced a decline in the late 2015 and early 2016 as a result of depressive prices in commodities and a feeble economic global recovery resulting in outflow of funds from Namibia (Brown *et al*., 2016). It also experience a decline early 2020 to late 2022 due the negative effect of the COVID-19 pandemic.

1.2 Statement of the problem

The NSX is a growing and developing equity market characterised by unsophisticated investors, high volatility, lack of transparency, severe regulations and reforms as well as relying heavily on the performance of the South African (SA) economy as most securities are dually listed on the Johannesburg Stock Exchange (NSX, 2019). Furthermore, the Namibian dollar (NAD) is pegged at par with the South African Rand (ZAR), at a ratio of 1 NAD to 1 ZAR. Thus, the Namibian economy in general and in turn the NSX are exposed to various external macro-economic shocks such as changes in South African monetary and exchange rate policies. Recently the SA economy has faced political instability and economic downturn with the real GDP growth rate shrinking from about 1.49% in 2018, the same year the current President Matamela Cyril Ramaphosa, officially took office from his predecessor Jacob Zuma, to about 0.11% in 2019 (World Bank, 2021). During the same period, the South African Rand depreciated on average against the United States Dollar (USD), on a quarterly basis from around

USD1:ZAR11.95 during the first quarter of 2018 to around USD1:ZAR14.71 during the last quarter of 2019 (BON, 2020). Exposure to such external shocks increases the risks of investors, thereby inducing herding behaviour especially if other investors are more informed than others (Gong & Dai, 2017). In this regard, herding can be viewed as additional risk factor as it distorts asset prices and their fundamentals values, which can lead to higher market volatility causing some bubbles and financial crashes in worst scenarios (Cakan & Balagyozyan, 2014). Thus, herding behaviour plays a major role in asset pricing models and the Efficient Market Hypothesis (EMH). It distorts the risk return distributions in the asset markets which leads to stock market instability and mispricing, thereby violating the market efficiency hypothesis. It is against this background the current study seeks to examine the existence of herd behaviour in the NSX on both the overall market and at sectoral levels and the influence of the changes in South African interest rates and exchange rates on herding in the aforementioned stock market.

1.3 Objectives of the study

The main objective of this study is to analyse the dynamics of herding behaviour in the NSX. The specific objectives of this study are:

- to identify the existence of herding behaviour in the NSX
- to identify the existence of sectoral herding behaviour in the NSX
- to examine the influence of SA macro-economic fluctuations on the herding behaviour in the NSX

1.4 Hypotheses of the study

This study is guided by the following alternative hypotheses:

Hypothesis 1: There is existence of overall market herding behaviour in the NSX

Hypothesis 2: There is existence of sectoral herding behaviour in the NSX

Hypothesis 3: Fluctuations in the South African macro-economic variables have significant influence on the herding behaviour in the NSX

1.5 Significance of the study

Although studies in the area of herding behaviour have been done in other countries, they remain limited in developing countries particularly in Namibia. Thus, academically the study may contribute to the existing literature and knowledge gap on herding behaviour. Furthermore, future researchers may gain additional information on herd behaviour in the financial markets. Apart from this, the current study may also assist the current and potential investors as well as management of firms listed on the NSX in the efficient financial asset allocation process and diversification of risk which may minimise financial bubbles and crashes in the worst scenario. Furthermore, the current study may also help Namibian policy makers in designing sound legislative framework which improves transparency and investor confidence in the capital markets in the country.

1.6 Limitation of the study

Due to the fact that literature on herding behaviour particularly in sub-Saharan Africa is very limited and the NSX still developing, getting access to some relevant databases and relevant statistics acted as a stumbling block and hampered this current study's completion timeframe. Furthermore, the inaccessibility of the comprehensive database on investors' private information made it impossible to examine the herding behaviour of specific individual and institutional investors relying on micro or proprietary data. To examine herding behaviour towards market consensus, this current relied on aggregate prices and market activity data in the NSX which is readily available. Thus, the results of this current study may not be generalised beyond the NSX from which the sample in this study was drawn.

1.7 Delimitation of the study

This study utilised the weekly and monthly closing prices, market capitalisation, Johannesburg Interbank Average Rate (JIBAR) 3 month yield rates and the United States Dollar (USD) to South African Rand (ZAR) exchange rates data for the period 1st January 2003 to 30th June 2023 due to data availability. Exemption from ethical clearance in carrying out this research was obtained from the Faculty of Commerce, Management and Law Decentralized Ethics Committee (DEC) (see Appendix A).

1.8 Chapter summary

Chapter 1 presented the introduction and orientation of the study, statement of the problem, research objectives and hypotheses of the study, significance of the study, limitations and delimitations of the study. Chapter 2 presents the theoretical and empirical literature related to herding behaviour. Chapter 3 examines overall market herding behaviour in the NSX. Chapter 4 examines sectoral herd behaviour in the NSX. Chapter

5 examines the influence of fluctuations the South African interest rates and exchange rates on herding behaviour in the NSX. Lastly, Chapter 6 concludes this study.

Chapter 2: Literature Review

2.1 Introduction

This chapter provides extensive elucidation of the theoretical and empirical literature underpinning herding behaviour and also enables the identification of the gap in literature in this study. This chapter forms the base for the methodologies utilised in this study.

2.2 Theoretical framework

Since the seminal work of Lakonishok *et al*. (1992), a number of studies have dealt with the reasons or drivers of herding behaviour. Some notable studies includes: Christie and Huang (1995); Demirer *et al*. (2010); Spyrou (2013); and Škrinjarić (2018) among others. Herding behaviour can simply be defined as an investment tool by which investors mimic the actions of others or market agreement (Bikhchandani & Sharma, 2001). In this regard, investors tend to mimic the actions of others or changes in the market whilst disregarding their own investment beliefs and information (Hwang & Salmon, 2004). The explicit explanation of herding behaviour can be traced back to the great work of Keynes (1936), who posited that investors mimic others merely due to the fear of reputational damage as result of such antagonistic behaviour on the market. However, elucidation of this behaviour gained more momentum in the late 1990s and early 2000s (Škrinjarić, 2018).

The reasons for herding behaviour can be split into the following two groups: a) Individual vs Institutional herding drivers; (b) Rational vs Irrational herding drivers;

a. Individual vs Institutional herding drivers

Herding behaviour among individuals tend to be much stronger compared to institutional herding. Moreso, individual herd behaviour is believed to be persistent overtime (Barber *et al*., 2009) and found to be positive and significantly correlated to market volatility (Venezia *et al*., 2011). Barber *et al.* (2009) indicated that psychological biases are the main drivers for individual herd behaviour. For example, biases can cause investors to buy the equities which have performed strongly recently, desist from selling equities which are being held for a loss, and to be net acquirers of those equities whose trading volume are abnormally high.

Institutional herding behaviour arises due to information asymmetry between investors regarding their trading strategies. Moreso, when performance evaluation is done for the managers against others as the basis for compensation, those managers do not want to picked out for having portfolios distinct to others (Škrinjarić, 2018).

b. Rational vs Irrational herding drivers

Some researchers are of the opinion that herd behaviour is rational under certain circumstances. For example, as pointed by Spyrou (2013) fund managers may follow the actions of others fund managers as a way of preserving their reputation and/ or getting rewarded (compensated). Younger market analysts or those with lower abilities may be scared of losing their job if they make some bold predictions not the same as others. The issue of herding can also be related to the issue of bank runs explained by Diamond and

Dybvig (1983). Depositors also contributes to bank runs during a banking crisis. As depositors see long queues at bank premises, they fear losing out on all the remaining funds if they don't join the queue early. Bikhchandani and Sharma (2001) differentiate between "spurious" herding and "intentional" herding. "Spurious" herding occurs when market participants make the same decisions as they face the same fundamental-based information sets whilst "intentional" herding involves market participants intentionally mimic the actions of others, for instance, in case of information cascades or as a way of preserving reputation and/ or protect compensation (Bikhchandani & Sharma, 2001). "Spurious" herding may result in an efficient outcome unlike the "intentional" herding. In worst scenarios, the latter may result in fragile financial markets, excess market volatility and systemic risk (Spyrou, 2013a).

From the rational view point, herding behaviour occurs due to informational, reputation and compensational concerns as discussed below:

i. Informational herding drivers

This occurs due to imperfect information whereby the lack of or excess of information relative to others leads to investors disregarding their own beliefs as pointed by Bikhchandani and Sharma (2001). Here investors or market participants get information by observing the trading activities of others (Bikhchandani *et al*., 1992). The investor may willingly decide to ignore his/her own information if he/she finds the externality to be too strong (Merli & Roger, 2013). Under exceptional circumstances, the investor's actions may no longer carry any information, but just only emanate from mimicking others' trading activities and information cascades would occur in such instance. Thus, informational cascades may occur when it is optimal for investors to mimic the observable actions of other investors, ignoring their own information (Bikhchandani *et al.*, 1992). For instance, it may be an optimal decision for investors that join the market in later stages to disregard their own private information and follow the investment actions of investors that entered the market earlier, as they believe the earlier investors holds some important private information. Informational cascades may affect perfectly rational investors and ultimately result in the emergence of market bubbles (Spyrou, 2013a). It is also imperative to note that informational cascades may be connected to partial or total blockages in information aggregation, amplified market fragility to even little informational shocks, fads and stampedes (Hirshleifer & Teoh, 2003).

ii. Reputation herding drivers

Reputational drivers are related to the principal-agent theory. It is a behaviour that is based on the fact that managers tend to hide in the herd and aspire to have their performance evaluated against a benchmark similar to others as this may allow them to cushion against poor market performance (Škrinjarić, 2018). By having their performance evaluated against a set benchmark such as the average performance of others or industry/market index performance, it may be tantalizing for them to mimic the set benchmark (Merli & Roger, 2013). Nonetheless, by taking that action, they tend to sacrifice the potential of earning above the market average gains as they just hedge themselves against a bad relative performance (Stein & Scharfstein, 1990). An individual investor loses some of his/her reputation by making a poor investment decision. However, a poor investment decision by all investors in a group, means no one individual will be picked out and the responsibility falls on the group not individual managers.

iii. Compensation herding drivers

The acuity of the abilities of market analysts affect their compensation. Market analysts tend to make uniform forecasts as others basing their analysis on previously published ones (Trueman, 1994). In this regard, to get similar results and ultimately higher compensation, those market analysts with lower abilities just mimic the results of those with higher ability, despite the fact that this behaviour is not supported by the private market analyst information. Trueman's theoretical model reveals that the forecasts by market analysts do not always reveal in an impartial way their private information but rather these forecasts are produced to be closer or similar to the expected ones. For instance, highly reputable market analysts have greater motivation to hide in the herd as a way of preserving their reputation. Furthermore, market analysts are likely to herd when there is greater discrepancy between public information and private information as well as when signals of private information among market analysts unveil positive correlation (Graham, 1999).

Some studies argues that market participants are irrational and their existence may lead to some market bubbles and herding behaviour. Psychological stimuli and restraints such as pressure from social circles to fit in a group are seen as the major drivers of herding behaviour according to the irrational viewpoint (Spyrou, 2013a). For example, social factors such as social conventions affect market participants and may drive them to follow the behaviour of others during times of uncertainty as pointed by Keynes (1936). On an empirical level, irrational or non-rational herd behaviour is extremely difficult to capture as it is driven by fashion and fads (Merli & Roger, 2013).

2.3 Herding behaviour measures

To test for the presence of herd behaviour a number of methodologies have been proposed in the literature. These empirical methodologies can be divided into two (2) major categories: 1) the studies that utilises micro or proprietary data; and (2) studies that utilised aggregate price and market activity . The first category investigates herd behaviour of the specific type of investors, whilst the latter category investigates market consensus herd behaviour.

2.3.1 Herding behaviour measures utilising the micro or proprietary data

The most popular studies in this are Lakonishok *et al.* (1992) and Sias (2004). One of the first institutional herding measure is the one suggested by Lakonishok *et al.* (1992) which hereafter referred to as the LSV measure. The idea underpinning the LSV measure is that herding at individual stock level occurs when there is an excess (disproportionate) of purchases or sales of an individual stock by the money managers. The LSV herding measure estimates herding behaviour as the proportion of net buyers relative to all the money managers trading a given stock minus an adjustment factor that falls with the rising active number of money managers for that given stock. This metric measure doesn't vary from time to time in the absence of herding but there should be significant cross-sectional variation in this metric in the presence of herd behaviour. Thus, the LSV herd measure is estimated as follows:

$$H(i) = \left|\frac{B(i)}{B(i)+S(i)} - p(t)\right| - AF(i) \qquad (2.1)$$

Where: H represents the LSV herd measure; $H(i)$ denotes the number of money managers who are considered net buyers; $S(i)$ denotes the number of money managers who are net sellers (that is, whose holdings declines); $p(t)$ denotes the expected proportion of money managers that buy in that quarter relative to the active number; and $AF(i)$ denotes the adjustment factor, which is the expected value of $|B/(B+S)-p|$ under the null hypothesis of herd behaviour. AF falls with the rising active number of money managers for that given stock (Lakonishok *et al.*, 1992).

Utilising the US 769 tax-exempt funds data and the LSV metric to examine herd behaviour and positive feedback trading , Lakonishok *et al.* (1992) found little evidence of herding behaviour or positive feedback trading. However, they found novel evidence of herd behaviour for the smaller stocks, although having no destablising effect on the prices of the stocks. In spite of its popularity, the LSV herd measure outline above is often criticised from a number of factors. More importantly, it does not allow for an evaluation of herd behaviour of a specific investors, and therefore, unable to evaluate the persistence of herd behaviour in the course of time at the investor level (Merli & Roger, 2013). Apart from this, it makes difficult to investigate what drives individual herd behaviour.

If institutional investors herd in the same securities as pointed by Sias (2004), their proportion that buys the current quarter will covary across securities with the proportion of those that bought the previous quarter. In this regard, the cross-sectional correlation between the demand for a security by these institutional investors the previous and current quarters is then used to evaluate herd behaviour. Sias begins by calculating the position of every institutional investor in each security as a proportion of the outstanding shares in that security at both the start and end of each quarter. An institutional investor is then classified as a seller (buyer) if the ownership decreases (increases) in that specific security. The portion of institutional investors who are defined as buyers is calculated for each security quarter. The described ratio is calculated as follows:

$$Raw\Delta_{k,t} = \frac{BI_{k,t}}{BI_{k,t}+SI_{k,t}} \tag{2.2}$$

Where: Raw denotes the raw fraction of buying institutional investors; BI denotes the number of institutional investors buying security k during quarter ; SI denotes the number of institutional investors selling security k during quarter t. As a way of allowing aggregation during the course of time and make a distinction between various market capitalisations and type of investors, the fraction of institutional investors buying security k during quarter t in the above Equation 2.1 is standardised by Sias as follows:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_{k,t}}}{\sigma(Raw\Delta_{k,t})} \tag{2.3}$$

The cross-sectional Equation 2.3 is then evaluated as follows:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{2.4}$$

The notion in the above equation is that if institutional investors mimic each other in and out of same asset or they follow own trades in the previous quarter, then there will be a positive correlation between the fraction of those buying in this quarter and those in the last quarter (Sias, 2004). The key distinction between the LSV herd measure and the Sias herd measure is that the former investigates in an indirect way for cross-sectional temporal dependence inside periods whilst the latter investigates directly whether institutions herd during the subsequent periods (Sias, 2004). Sias (2004) finds that institutional investors tend to follow momentum investment strategies and mimic others in buying and selling similar securities, although the study finds little evidence of their herding behaviour emanating from the momentum investment strategy. Sias (2004) finds no evidence of prices being driven away from their fundamental values by herd behaviour.

2.3.2 Herding behaviour measures utilising aggregate market price

The most common studies in this category are Christie and Huang (1995), (Chang *et al.*, (2000) and Hwang and Salmon (2004) henceforth referred to as CH, CCK and HS respectively. CH suggest that during times of extreme market conditions, investors are most likely to disregard their own investment beliefs and mimic the actions of others. Thus, the stock return dispersions will be relatively low as the stock returns tend not deviate very far from the market returns. The capital asset pricing model suggest increase in return dispersion when there is difference in equity sensitivity towards the market (Spyrou, 2013a). CH utilises the cross-sectional standard deviation (CSSD) to proxy herding as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t}-R_{m,t}\right)^2}{N-1}} \tag{2.5}$$

Where: $R_{i,t}$ denotes the is the security return of firm i at time t; $R_{m,t}$ is the is the market return at time t. Thus, the CH metric above captures closeness to the market average of a particular security return. As a way of determining whether the stock return dispersions are significantly lower during the extreme market conditions, CH employed the following equation:

$$CSSD_t = \alpha + \delta^L D_t^L + \delta^U D_t^U + \varepsilon_t \quad (2.6)$$

Where: D_t^L is a dummy that takes the value of one (1) if the market return on day t falls in the extreme lower tail of the returns distribution and zero (0) otherwise; D_t^U is the dummy that takes the value of one (1) if the market return on day t falls in the extreme upper tail of the market distribution and zero (0) otherwise, and ε_t is the white noise error term. The dummy variable in the above equation is utilised to capture distinct investor actions during extreme negative and positive market conditions in relation to normal conditions in the market. CH used the arbitrary one percent (1%) and five percent (5%) and ten percent (10%) cut-off points as the criteria to capture extreme market movements. Statistically significant negative coefficients of δ^L or δ^U in Equations 2.6 above suggest presence of herding during extreme market conditions whilst positive coefficients implies the rational asset pricing assumption holds.

However, the model proposed by Christie and Huang (1995) has often been criticised for a number of reasons. Firstly, they assumed the herding behaviour can be captured through linear relationship between the CSSD and the market returns which may not also be the case as has been proved by a number of other researchers such as Chang *et al*. (2000), Guney, Kallinterakis and Komba (2017) and Vo and Phan (2017) among others. The relationship between equity return dispersion and market volatility is linear if the rational asset pricing models holds. Chang *et al.* (2000) discovered that the presence of herding behaviour indicates violation of the rational pricing models. Thus, during periods of relatively big price movements, if investors follow the aggregate market behaviour at the expense of their own investment strategies, then the linear relationship becomes nonlinear increasing or even decreasing. Secondly, there is no consensus on what is "extreme". Christie and Huang (1995) used an arbitrary 1%, 5% and 10% as the cut off points for defining the extreme movements in the market returns. However, this may differ between investors.

Thirdly, their model point to the fact that herding behaviour can only be present during extreme market movement a fact which has been refuted by other researchers like Chiang, Li and Tan (2010) and Tan *et al*. (2008). Thus, herding behaviour may be witnessed during the entire market return distribution not only during the extreme periods and become more ubiquitous during market stress or abnormal market conditions. Furthermore, the CH metric measure described above can be sensitive to outliers and often produces inconsistent results.

To overcome some drawbacks of the CH model, CCK extended the work of CH and proposes the use of cross-sectional absolute standard deviation (CSAD) which is more robust to outliers as an alternative measure of herding behaviour to the traditional CSSD. CCK posits that if market participants track the aggregate market action during times of high average price movements, then the assumed monotonically increasing and linear relationship that exist between return dispersion (CSAD) and average market return collapses and becomes non-linearly increasing or even declining (negative). To estimate the relationship between CSAD and the average market return, CCK employed a non-linear model. Following the conditional version of Black (1972)'s Capital Asset Pricing Model (CAPM), they expressed the expected CSAD of equity returns (ECSAD) in time t , as below:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m|E_t(R_m - \gamma_0) \tag{2.7}$$

Where: R_m denotes the market portfolio returns; β_i denotes the time variant systematic risk measure of any security i ; β_m denotes an equally weighted market portfolio's systematic risk; γ_0 denotes the zero-beta portfolio's return. The expression below by CCK illustrates the linear and increasing relationship between return dispersion and the time-varying expected market returns:

$$\frac{\partial ECSAD}{\partial E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| > 0 \tag{2.8}$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(R_m)^2} = 0 \tag{2.9}$$

Any non-linearity possibility between stock return dispersion and the average market returns can then be captured by a parameter as proposed by CCK. To proxy the unobservable $ECSAD_t$, they utilise the cross-sectional absolute deviation at period t ($CSAD_t$). The average value of the deviation in absolute terms (VDA) of stock i relative to the equally weighted market portfolio's expected return. The idea behind this method is that there should be less than proportionate increase or even decline in the cross-sectional absolute deviation (CSAD) metric in the event of existence of herd behaviour during times of extreme market volatility. It is imperative to note that herding behaviour is diagnosed by the CSAD and average market return relationship.

In this regard, the quadratic term of the market return is incorporated in the model to take cognisance of non-linearity of the relationship between the cross section deviations of the returns and the market returns. Thus, the existence of herding behaviour is estimated as follows:

$$CSAD_t = \psi_0 + \psi_1 |R_{m,t}| + \psi_2 R_{m,t}^2 + \varepsilon_t \tag{2.10}$$

The left hand variable, $CSAD_t$ is a cross-sectional absolute deviation used to measure dispersion at time t. $|R_{m,t}|$ is the absolute value of the market returns. A statistically significant negative ψ_2 in Equation (2.10) indicates presence of herding behaviour as pointed by Economou, Katsikas and Vickers (2016) and Litimi (2017). $CSAD_t$ is calculated as follows:

$$CSAD_t = \sqrt{\frac{\sum_{i=1}^{N} \left(R_{i,t} - R_{m,t}\right)^2}{(N-1)}} \tag{2.11}$$

Where: $R_{i,t}$ is the stock return of firm i at time t and $R_{m,t}$ is the market return at time t. The individual stock returns $R_{i,t}$ obtained by taking the log differences of the closing prices. Thus, $R_{i,t} = 100 \times [\ln(P_t) - \ln(P_{t-1})]$ whereby P_t indicates the closing price at time t and P_{t-1} indicates the closing price at time $t-1$.

However, herding behaviour sometimes is affected by the size of the stocks. Smaller firms tend to have greater herding behaviour effects compared to larger firms due to poor flow of information in the former (Lakonishok *et al.*, 1992). This leads to overstatement of the impact of these smaller firms in the equally weighted stock return models. To control for the effects of size on herding behaviour, Equation (2.11) can be estimated using value-weighted as follows:

$$CSAD_t = \sum_{i=1}^{N} |w_{i,t} r_{i,t} - r_{m,t}| \tag{2.12}$$

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} r_{i,t} \tag{2.13}$$

Where: $w_{i,t}r_{i,t}$ is the weighted stock return of firm i at time t. The weight is derived as the fraction of a stock market capitalisation on day t divided by the total market capitalisation of all n traded stocks on day t.

The major criticism of the Equation (2.10) above proposed by Chang *et al*. (2000) is the possibility of high multicollinearity between the two regressors, that is, market returns $R_{m,t}$ and the squared of the market returns $R_{m,t}^2$. This may lead to parameter estimates which are inaccurate and problematic to interpret although the OLS estimators remains Best Linear Unbiased Efficient (BLUE) under such scenario as pointed by Yao, Ma and He (2014). As a way of reducing multicollinearity between the regressors and improving the results Yao *et al*. (2014) modified the Chang *et al*. (2000) model as follows:

$$CSAD_t = \psi_0 + \psi_1|R_{m,t}| + \psi_2\left(R_{m,t} - \bar{R}_m\right)^2 + \varepsilon_t \qquad (2.14)$$

The term $\bar{R}_m$ in Equation (2.14) represents the arithmetic mean of $R_{m,t}$. It is imperative to note that time series data sometimes tend to be auto-correlated and if not properly addressed may lead to biased estimated parameters. Some researchers like Economou *et al.* (2016), My and Truong (2011) and Škrinjarić (2018) used the Newey and West (1987) consistent standard errors to address the issue of heteroscedasticity and autocorrelation. Lao and Singh (2011) and Yao *et al*. (2014) added a 1 day lag of the dependent variable to Equation (2.15) as a regressor as a way of improving the results and address the issue of serial correlation as follows:

$$CSAD_t = \psi_0 + \psi_1|R_{m,t}| + \psi_2\left(R_{m,t} - \bar{R}_m\right)^2 + \psi_3 CSAD_{t-1} + \varepsilon_t \qquad (2.15)$$

As noted by Bikhchandani and Sharma (2001) herding behaviour sometimes can be "spurious". The LSV, CSSD and CSAD described above maybe biased in detecting herd behaviour as they fail to into consideration common information in the market like market fundamental. They not able to differentiate between "spurious" and "intentional" herding. Taking cognisance of market innovations affecting all investors, Hwang and Salmon (2004) then proposed the HS state-space model that takes into account these fundamentals market innovation factors. The HS is based on the cross sectional variability of factor sensitivities as opposed to market returns (Demirer *et al*., 2010). HS assumes bias in the CAPM estimates and propose the state-space method as a way of quantifying the deviation between the parameter of the real market and that of the equilibrium market. (Xie *et al*., 2015). The cross sectional standard deviance (CSSD) of time variant beta is defined as follows:

$$\mathrm{Std}_c(\beta_{imt}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\beta_{imt} - \mathrm{E}_c(\beta_{imt})\right)^2} \qquad (2.16)$$

The cross sectional beta has low volatility since the asset beta has low long term volatility too. HS assumes the cross sectional beta is an amalgamation of an average term and an equal variance stochastic error term:

$$\log \mathrm{Std}_c\,(\beta_{imt}) = \mu_m + \nu_{mt} \qquad (2.17)$$

Where: $\mu_m = \mathrm{E} \log \mathrm{Std}_c(\beta_{imt})$ and $\nu_{mt} \sim i.i.d.(0, \sigma_{mv}^2)$

HS asserts that during herd periods, $\mathrm{Std}_c(\beta_{imt})$ should be different from the biased value $\mathrm{Std}_c(\beta_{imt}^b)$. Furthermore, $h_{mt} \in [0,1]$ is defined as the herding factor, that satisfies

$\mathrm{Std}_c(\beta_{imt}^b) = \mathrm{Std}_c(\beta_{imt})(1 - h_{mt})$. A sign of no herd behaviour is denoted by $h_{mt} = 0$ and complete herd behaviour when $h_{mt} = 1$. Some herd behaviours is indicated when $0 < h_{mt} < 1$. HS also suggest that:

$$\log \mathrm{Std}_c(\beta_{imt}^b) = \log \mathrm{Std}_c\,(\beta_{imt}) \tag{2.18}$$

By letting $\mathrm{H}_{mt} \triangleq \log\,(1\text{-}h_{mt})$, thus evidence of herd behaviour is provided by significantly negative H_{mt}. The assumption is that H_{mt} follows a stationary AR (1) and the state space model 1 is given as follows:

$$\log \mathrm{Std}_c(\beta_{imt}^b) = \mu_m + H_{mt} + \nu_{mt} \tag{2.19}$$

$$H_{mt} = \phi_n H_{m(t-1)} + \eta_{mt} \tag{2.20}$$

Where: $H_{mt} = \log(1 - h_{mt})$ and $\eta_{mt} \sim i.i.d.(0, \sigma_{m\eta}^2)$

Equations 2.19 and 2.20 are the classic state-space models whose parameters can be estimated with Kalman Filter. $\sigma_{m\eta}^2 = 0$ equivalently means $H_{mt} = 0$ thereby implying absence of herd behaviour. A significant $\sigma_{m\eta}^2$ value is regarded as novel evidence of herd behaviour while a significant $\phi > 0$ supports this particular first-order autoregressive structure. Another augmented model can be formulated by adding the two (2) regressors market volatility, $\log \sigma_{mt}$ and return, r_{mt} in Equation 2.19. Thus, a state space model 2 is given as follows:

$$\log \mathrm{Std}_c(\beta_{imt}^b) = \mu_m + H_{mt} + c_{m1} \log \sigma_{mt} + c_{m2} r_{mt} + \nu_{mt} \tag{2.21}$$

In a similar way, a significant $\sigma_{m\eta}^2$ value is regarded as novel evidence of herd behaviour while significant $\phi > 0$ supports the autoregressive structure in the model.

Instead of reporting no herd behaviour as reported by Christie and Huang (1995), HS reports significant and persistent herd behaviour in the South Korean and US stock markets, independent of market conditions and macroeconomic fundamentals. They also report that herd behaviour tend to decline with market stress. However, the HS state space model has some implicit flaws which makes it hardly applied in practice:

i. The assumption that $\mathrm{H}_{m,t}$ follows a stationary AR(1) process is a more of a mere fallacy rather than factual. Although such a feasible guess can make calculations simplified, however, without a better scrutiny of higher order effects, the assumption may not hold in real markets scenarios and may even convey information which is wrong.

ii. Empirically, the term is $\sigma^2_{m\eta}$ is seldom insignificant. This may point to the fact the herd behaviour exists all the time or the inadequacy of the HS model' discrimination power.

iii. The cross sectional variance of time variant beta is taken as the regressand in the HS model. Nevertheless, there is no unanimity or an effective approach to get the time-variant beta. Regressions are done using monthly data to obtain the time variant beta in HS model which may certainly dents the efficiency of data of usage. Other methods may be inappropriate to obtain the beta and repetitions of the process may lead to expanded errors.

Comparable to HS, Xie *et al*.(2015) begin from the Arbitrage Pricing Theory(APT) and suggest a Weighted Cross-Sectional Variance (WCSV) measure to test herd behaviour pattern in the Chinese A-share market. They detect strong herd behaviour after the 2007-

2008 Global Financial Crisis. Despite the WCSV being a new method for detecting herding behaviour, Xie *et al*.(2015) acknowledged that this method is not complete yet which makes its practical applicability questionable. Although, the HS and WCSV measures mentioned above considers the innovative market fundamentals to distinguish “spurious” herd behaviour, they are not capable of differentiating herd behaviour from autonomous changes in investors action at micro-foundation as pointed by Chen and Ru (2019). In this regard, the individual investors may be seen as imitating others but the perceived switching herd behaviour may be as a result of random autonomous change of the individual investor which may not be related to fundamental market factors. Thus, Chen and Ru (2019) proposed the Heterogeneous agents model (HAM) measure to examine herd behaviour at micro-level. Analysing individual investor herd behaviour for the Chinese Stock market, Chen and Ru (2019) find evidence of herding particularly during the 2015 crash for both the large and small capitalisation equities. Large stocks are found to exhibit stronger herd behaviour before the crash than the small equities. However, the small stocks exhibit stronger herd behaviour than large stock during and after the 2015 crash. Although, the HAM is critical in solving some limitations of the current existing herd measure, the inaccessibility of some comprehensive individual investor information in sub-Saharan Africa stock markets particularly the Namibian Securities Exchange (NSX) hampers its practical applicability.

2.4 Theoretical gaps and empirical limitations

Having reviewed a number of studies on the theoretical and empirical level in this study on herding behaviour the following main conclusions emerge from the discussion. First, the debate on the empirical level remains inconclusive. Concerning institutional herd behaviour on one side some studies like Lakonishok *et al*. (1992) and Christie and Huang (1995) find limited evidence of herd behaviour , whilst on the other side some studies like Sias (2004) finds novel evidence of herd behaviour. Regarding market consensus herding, some studies like Hwang and Salmon (2004) find novel evidence of herd behaviour in the US and South Korean equity markets, whilst on the other hand some studies like Chang *et al.* (2000) find no evidence of herding behaviour in the US and Hong Kong Equity markets, partial herd behaviour evidence in the Japanese Equity market and novel evidence of herd behaviour in the South Korean and Taiwan Equity markets.

Secondly, the currently existing herd behaviour measures are marred by some limitations which can also be a possible explanation for the inconclusive and inconsistent empirical results. For instance, there are some drawbacks for the LSV metric utilised by some researchers despite it providing some valuable insights into the behaviour of fund managers. The LSV drawbacks include that: it may suggest presence of herd behaviour when only a number of market participants are active; there is no separation of the fund managers that trail their own trading strategy and those that mimic others; it does not directly test for dependence in institutional demand; it assumes selling is for short time and requires one to have access to a meticulous information regarding fund managers which may be unavailable (Sias, 2004; Hwang & Salmon, 2004)

Apart from these, the LSV measure is not able to reveal herd behaviour intensity since it does not take into consideration trading volume and also does not tell whether the same fund managers herd overtime as pointed by Bikhchandani and Sharma (2001).

Furthermore, the LSV metric is biased downwards and the bias tend to decrease with the number of those traders who are active (Merli & Roger, 2013). The CH herd measure and other comparable measures merely investigate one specific form of herd behaviour and overlooks herd behaviour in other contexts. Thus, its application and if results reveal absence of herd behaviour, one must take note that what is rejected is only herd behaviour towards the market harmony (Spyrou, 2013a).

Another restraint concerning the current existing measures on institutional herd behaviour emanate from the heterogeneity of the institutional investors. The institutional investors may include but not limited to: pension and insurance companies; investment banks; unit trusts; mutual funds; and hedge funds among others. There is heterogeneity even within each type/form of fund. Taking mutual funds as an example, it is such characterised by so many investment styles and strategies such as momentum strategy, fund of funds, growth vs value, index tracking, diversified fund, contrarian investment style, technology equities, quantitative investment strategies and emerging markets investments among others. Thus, detecting herd behaviour for the mutual funds may be a tough assignment. The managers of funds maybe herding on different investment strategies and styles but no herding maybe detected if they are investigated as a group as their strategies and styles may knock out each other. For example, the momentum and contrarian investment managers having the same investment horizons may herd on different styles but no herding maybe detected if their transactions are aggregated together.

Thirdly, many empirical studies do not test whether herd behaviour is time-variant aspect. An important question then arises under this circumstance: Are the reasons for herding the same over time? As pointed by Baddeley (2010) herding behaviour may be due to the interface of cognitive and emotional influences.

Finally, discrepancy exists between theoretical predictions of herd behaviour and advancement of suitable methodologies to evaluate those predictions. If one takes informational cascades for instance, some theoretical models assume either concurrent or sequential trading. Thus, to comprehend informational cascades and partial or total blockages in information aggregation, a wide range of theoretical aspects such as asset pricing endogeneity, the importance of trading biases like locality bias, transactions costs, financial markets learning rates, the cost of acquiring information, access to vital information, the market participants' motive for trading both speculative and non-speculative motives among others. Without having access to comprehensive databases on private information for the investors prior to any trading, their reasons for mimicking others during trade and the dominant biases during their decision making processes, empirically testing most of these highlighted issues maybe a daunting task. A lot of assumptions are involved in empirical testing and can only be carried out indirectly. Thus, many empirical studies on herd behaviour embrace approaches that can quantify the transactions of investors and clustering in investment decision making. Nonetheless, clustering in investment decision making may be as a result of a number of reasons.

2.5 Conclusions

In a nutshell this chapter examined the theoretical and empirical literature underpinning herding behaviour dynamics. The inaccessibility of a comprehensive database on investors' micro-data such as private information means this current study focuses on herding behaviour measure employing the aggregate prices and market activity data which is readily available in the NSX. Both the traditional and unconventional herding measures discussed above have their own benefits and flaws. Although the CH and CCK are criticised for being too unrealistic to represent time-variant herd behaviour patterns using constant betas, in recent times many researchers have applied and enriched the CH and CCK models with some representative empirical findings. Thus, to improve the CH and CCK models, this current study goes a step further and applies the time-varying transition probability Markov regime switching model to analyse the time variant nature of herding behaviour which is one grey area which remains untapped by many researchers.

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Chapter 3: Herding behaviour in the Namibian Securities Exchange: A Markov Regime Switching Model Approach

Abstract

This research examines the existence of overall herding behaviour in the Namibian Securities Exchange (NSX) for the period 1st January 2003 to 30th June 2023 using both the weekly and monthly data series. The Markov two-Regime Switching Model (MRSM) approach is utilised to estimate equations in this study. This study employs the equally and value weighted cross sectional absolute standard deviation (CSAD) proposed by Chang *et al.* (2000) as the proxy for herding behaviour. The static approach as the benchmark model reveals absence of herding behaviour for the overall period under review. However, the MRSM approach provides evidence of herding behaviour in the volatile regime in line with theory and other previous studies. Thus, it is necessary for the market participants to form larger portfolio of securities in order to realise the same goal of diversification.

Key words:

Cross sectional absolute standard deviation, Herding behaviour, Markov two-Regime Switching Model, Namibian Securities Exchange, and Static approach

3.1 Introduction

Herding behaviour can be viewed as the tendency by market participants to imitate the investment actions of others whilst ignoring their own convictions or beliefs as noted by Filip *et al*. (2015). This phenomenon has great bearing on both the stock market and financial system. As investors herding, stock prices deviates from their fundamental values which can lead to some speculative bubbles and the prospect of profiteering from arbitrage (Vo & Phan, 2017). Vo and Phan (2017) further noted that the prolonged existence of herding behaviour and the inability of stock prices to readjust to their fundamental values may lead to market instability and inefficiency and financial system collapse in the worst scenario. The stock market is assumed to be efficient if the stock prices reflect all the relevant information both public and private.

The topic on herding behaviour continues to attract attention particularly after the 2007-2009 Global Financial Crisis and the recent Covid-19 pandemic due to its impact on the stock market and financial system. Herding behaviour is believed to be the cause of market volatility, financial markets instability and financial system brittleness. This study further throws light on the existence of herding behaviour in the emerging markets with a focus on the Namibian Securities Exchange (NSX).

This study is motivated by a number of factors. Firstly, the existing literature on the existence of herding behaviour in the emerging markets is inconclusive and limited especially in Namibia. Thus, further investigation is required to provide more insight on the herding behaviour in the emerging markets particularly in the African context. Most of the existing literature on herd behaviour focuses on the developed markets yet the phenomenon is believed to be more prominent in the emerging markets due to stronger information asymmetry as pointed by Vo and Phan (2017) . Furthermore, due to globalisation, emerging stock markets are gradually playing a major role in the development of global financial markets.

Secondly, since its inception in 1992 the NSX has witnessed low liquidity due to a number of factors chief among them poor corporate governance of firms listed, regulatory constraints and poor quality of information relating to disclosure of financial statements (Matongela & Karodia, 2015). All these lead to lack of transparency in the NSX of which non-transparency of the stock market is highlighted by Bikhchandani, Hirshleifer and Welch (1992) as one of the major drivers of herding behaviour. Furthermore, the NSX is greatly affected by movements in other stock markets like the Johannesburg Stock Exchange (JSE) as most equities are dually listed on both the stock exchanges and therefore attracts a lot of investors. It is against all those mentioned characteristics that a further investigation is required to ascertain the presence and extend of the herding behaviour in the aforementioned equity market.

Thirdly, to the best of the researcher's knowledge, this is the first study to investigate herding behaviour in the NSX utilising the Markov Regime Switching Model (MRSM) approach. The only other study done so far to investigate herding behaviour in the NSX is by Guney et al. (2017). However, Guney *et al.* (2017) used daily data employing the OLS method which is believed to be inferior compared to the MRSM method used in this current study. In this regard, this current study contributes greatly to the existing literature on herding behaviour in the emerging markets particularly the African context. The rest of this chapter is structured as follows: section 3.2 highlights the literature review, section 3.3 presents the research methodology, section 3.4 reports the results and discussion of the study and section 3.5 concludes and provide policy implications of the study.

3.2 Literature review

To date there is a large amount of literature on herding behaviour. Some studies focus on the theoretical aspects while others on empirical side. Those on theoretical aspects like Bikhchandani and Sharma (2001) and Spyrou (2013) focus on the herding behaviour concepts and its classifications. Others focus on the drivers of herding behaviour and how it impacts the financial system. Some notable studies like Stein and Scharfstein (1990), Bikhchandani and Sharma (2001), Spyrou (2013) and Hsieh (2013) point out that herd behaviour causes the stock prices to deviate from their fundamental values and ultimately destabilises the financial markets. However, others like Hirshleifer and Hong Teoh (2003) asserts that herd behaviour improves market efficiency as stock prices adjust quickly to the new information.

Empirically, a number of studies has far been carried out particularly in the developed markets to analyse the herding behaviour existence. Some of the notable studies are summarized in Table 3.1 below. Those from the European context include Filip *et al.* (2015), Cakan and Balagyozyan (2016), Economou *et al*. (2016), Litimi (2017) and Škrinjarić (2018). Filip *et al*. (2015) analyses the existence of herding behaviour for the Central and South Eastern Europe (CEE) countries covering Czech Republic, Poland, Hungary, Romania and Bulgaria. They employ the CSAD herding measure proposed by Chang *et al.* (2000). The authors find evidence of herding behaviour in all the sectors save for Poland. Furthermore, herding behaviour is found to be more pronounced in period of market decline similar to results by Economou *et al*. (2016) for the Athens Stock Exchange employing also the CSAD herding measure and also the Quantile Regression method. However, these results were in contrast to the finding by Cakan and Balagyozyan (2016) for the Turkish stock market. Cakan and Balagyozyan (2016) find herding behaviour to be more pronounced during the rising market conditions. Despite employing the CSAD herding measure employing both the QR and OLS method, Škrinjarić (2018) finds no evidence of herding behaviour in the Zagreb Stock Exchange (ZSE). This results also supports the finding by Litimi (2017) for the French Stock market for all the whole market although it's found to be present in consumer good, consumer services, financials, oil and gas and others sectors and also during crises periods.

From the Asian context, the notable studies include but not limited to: Lao and Singh (2011); My and Truong (2011); Yao *et al*. (2014); Lee *et al*. (2015); Ramadan (2015); Vo and Phan (2017); and Chaffai and Medhioub (2018). Employing the CSAD herding measure, Lao and Singh (2011) found evidence of herding behaviour in both the Chinese and Indian Stock markets. However, for the Chinese Stock market it's found to be more pronounced in the market decline. This finding is also similar to that by Yao *et al*. (2014), Lee *et al*. (2015) and Vo and Phan (2017). For the Indian stock market, Lao and Singh (2011) find herding behaviour to be more pronounced during rising markets than falling markets. This concurs to the finding by My and Truong (2011) for the Vietnamese Stock market and Chaffai and Medhioub (2018) for the Gulf Cooperation Council (GCC) Islamic stock market covering Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab

Emirates. Furthermore, employing the GARCH models, My and Truong (2011) find herding behaviour to be more pronounced in the extreme upwards markets.

On the African context, the notable studies include: Seetharam and Britten (2013); Ababio and Mwamba (2017); and Guney *et al*., (2017). Employing the CSAD herding measure, the study by Guney *et al*. (2017) find evidence of herding behaviour for all the countries covering Bourse Régionale des Valeurs Mobilières SA (Benin, Burkina Faso, Guinea Bissau, Côte d'Ivoire, Mali, Niger, Senegal, Togo), Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania and Zambia. This finding corroborates with Ababio and Mwamba (2017), but in contrast to Seetharam and Britten (2013) for the Johannesburg Stock Exchange's (JSE). Seetharam and Britten (2013) finds absence of herding behaviour in an overall study, but present in extreme bearish conditions than in extreme bullish conditions employing the CSSD, CSAD and Hwang and Salmon herding measure. Employing the CSAD herding measure and the QR method, Ababio and Mwamba (2017) find evidence of herding behaviour in the banking (when market is falling) and real estate sectors (when market is rising). For the entire financial industry, herding is found during extreme upmarket period. Despite the effort so far, the literature on herd behaviour in the African context is still limited, particularly for the NSX which is the major contribution of this current study.

Table 3.1: Summary of the empirical studies on herding behaviour

Country	Authors	Period	Methodology	Conclusion
Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates	Chaffai and Medhioub (2018)	Daily data for the period 2010-2016	QR and GARCH models employing the CCK herding measure	Results revealed evidence of herding behaviour in the Gulf Cooperation Council (GCC) Islamic stock market. More so, it existed during upward market periods only.
Bourse Régionale des Valeurs Mobilières(BRVM)(Benin, Burkina Faso, Guinea Bissau, Côte d'Ivoire, Mali, Niger, Senegal, Togo) Botswana, Ghana, Kenya, Namibia, Nigeria, Tanzania, Zambia	Guney *et al*. (2017)	Daily data for the period 2002-2015	OLS employing the CCK herding measure	The results revealed evidence of herding behaviour during both the up and down markets for all the countries using both equal and value weighted returns. The results also revealed presence of herding behaviour during the 2007-2009 Global Financial Crisis for Ghana, Kenya, Namibia, Tanzania and Zambia for both the equally and value weighted returns.
Central and South Eastern Europe(CEE) (Czech Republic, Poland, Hungary, Romania and Bulgaria)	Filip *et al*. (2015)	Daily data for the period 2008-2010	OLS employing the CCK herding measure	The results revealed presence of herding behaviour in all the sectors except for Poland. Furthermore, its being more pronounced in the period of market decline. The global financial crisis of 2007-2009 is found to have no impact on herding behaviour.
China	Yao *et al*. (2014)	Daily and weekly data	OLS employing the CH and CCK herding measures	The results revealed evidence of herding behaviour being more pronounced in periods of market decline for both the A-share and the Shanghai B- share markets.

		for the period 1999-2008		
China and India	Lao and Singh (2011)	Daily and weekly data for the period 1999-2009	OLS using the CCK herding measure	The results revealed presence of herding behaviour in both the markets. In the Chinese market, the herd behaviour is greater when the market is falling while in the Indian market its greater during upswings in the market conditions
Chinese A-Share market	Fu and Wu (2020)	Daily and monthly stock prices from 1999-2016	Two-state Markov Switching model employing the CH herding measure	The results revealed novel evidence of herding during the volatile regime for the whole market
Croatia	Škrinjarić (2018)	Daily data for the period 2014-2018	QR and OLS employing the modified CCK herding measure	The results revealed very weak to non-existence of herd behaviour in the Zagreb Stock Exchange (ZSE).
France	Litimi (2017)	Daily data for the period 2000 to 2016	OLS and GARCH employing the modified CCK herding measure	The results indicate absence of herding behaviour in the whole market but present in consumer good, consumer services, financials, oil and gas and others sectors. Furthermore, the results indicate presence of herding behaviour during crises.
Greece	Economou *et al.*, (2016)	Daily data for the period 2007-2015	QR and OLS using CCK herding measure	The results revealed presence of herd behaviour in the Athens Stock Exchange for the equally weighted returns being stronger in down markets. The results also revealed herd behaviour being present in higher quantiles of the cross sectional return dispersion.
Hong Kong	Lam and Qiao (2015)	Daily data from 1986-2007	OLS and GARCH employing the CH and CCK herding measures	The OLS and GARCH results revealed evidence of herding for the whole market

Jordan	Ramadan (2015)	Daily data for the period 2000-2014	OLS employing CCK herding measure	The results revealed existence of herding behaviour in the Amman Stock Exchange
Jordan	Elshqirat (2019)	Daily data from 2000-2008	OLS employing the CCK herding measure	The OLS results revealed absence of herding for the overall market
Malaysia	Mand and Sifat (2021)	Daily data for period 1995-2016	Two-state Markov Switching employing CH and CCK herding measure	The results revealed evidence of herding behaviour for the overall market
Pakistan	Ahmed *et al.* (2019)	Monthly data from 2013-2008	Employing HS herding measure	The results revealed evidence of herding for the whole market
South Africa	Seetharam and Britten (2013)	Monthly data for the 1995-2011	OLS employing CH, CCK and HS herding measures	The results revealed absence of herding behaviour overall, but present in extreme market conditions mostly during bearish market conditions than bullish market conditions.
Taiwan	Lee *et al*. (2015)	Daily data for the period 2000-2012	QR employing CH and CCK herding measures	The results revealed evidence of herding behaviour in the Taiwan stock market for all the quantiles being stronger when markets are down than during upswing. However, the 2007-2009 Global Financial Crisis is found to have no effect on herding behaviour in the Taiwan market.
Turkey	Cakan and Balagyozyan (2016)	Daily data for the period 2002-2014	OLS employing the CCK herding measures	The results revealed evidence of herding behaviour in all industrial sectors of the Turkish stock market during both rising and falling markets. However, it’s more pronounced during the rising markets.

US-listed Real Estate Investments Trusts (REITS)	Babalos *et al*. (2015)	Daily returns for period 2004-2013	Three-state Markov Switching model employing the CCK herding measure	The results revealed evidence of herding behaviour for the whole market during the crash regime
Vietnam	My and Truong (2011)	Daily data for the period 2002-2007	OLS and GARCH models employing the CCK herding behaviour	The results of the OLS indicated absence of herding behaviour in the Vietnamese Stock market. However, the results of the GARCH (1, 1) model revealed evidence of the herding behaviour in the overall market. Herding behaviour is also found to be more pronounced in the rising markets than falling markets. Furthermore, it's more pronounced in the extreme upwards markets.
Vietnam	Vo and Phan (2017)	Daily, weekly and monthly data for the period 2005-2015	OLS using CH and CCK models herding measures	Herding behaviour exist in the Vietnam equity market for the daily and weekly data. However, no evidence of herding was found for the monthly data set. The results also provided evidence of herding behaviour being more pronounced in down market than in up market conditions. The recent global meltdown of 2007-2009 is found to have no impact on herding behaviour.

Note: OLS, QR, GARCH, CH, CCK, HS refers to Ordinary Least Squares; Quantile Regression; Generalised autoregressive conditional heteroscedasticity; Christie and Huang; Chang, Cheng and Khorana; Hwang and Salmon

3.3 Methodology

3.3.1 Static approach for testing herding behaviour

As discussed in the previous chapter, this study follows the approach by Chang *et al.* (2000) and Yao *et al*. (2014) with minor adjustments in specifying the static approach in detecting herding behaviour as follows:

$$Dispersion_t = \alpha + \varphi_1 \left| R_{m,t} \right| + \varphi_2 R_{m,t}^2 + Dispersion_{t-1} + \varepsilon_t \quad (3.1)$$

Since in this study we intended to subject both the equally and value weighted CSAD to the static model, a general notation $Dispersion_t$ is used in place of these variable as illustrated above.

3.3.2 Regime switching approach for testing herding behaviour

Having examined herding behaviour under the static approach above, this section outlines the regime switching approach of capturing herd behaviour. The benchmark model in Equation (3.1) above is static as it assumes constant parameters and therefore not able to detect possible structural changes. This may ultimately lead to model misspecification (Balcilar & Demirer, 2015). The regime dependent approach is gaining popularity in recent times due to a number of reasons. Firstly, the regime switching model is considered superior to linear models, due to its ability track beyond traditional stylised facts (Babalos *et al*., 2015). Secondly, the model is flexible and able to capture herd behaviour under different states as pointed by Mand and Sifat (2021). Thirdly, herd behaviour can be driven by a number of factors save for returns which often depends on market conditions. As pointed Mand and Sifat (2021) during market turmoil speculative tendencies may lead to market uncertainties which can precipitate a feedback loop. Some previous notable researchers like Christie and Huang (1995), Chiang and Zheng (2010) and Economou *et al*. (2016) attempted to add some dummy variables as a way distinguishing market states. This was done as a way of specifying the time variations and the regime switching property of herding behaviour (Fu & Wu, 2020).

In the above scenario, experts' opinions tend to be the benchmark used in selecting the breaking points of the dummy variable which may be deemed rudimentary as pointed by Fu and Wu (2020). Schmitt and Westerhoff (2017) came up with threshold model to distinguish speculators' behaviour. They concluded that an observable exogenous process directly determines the two (2) regime states. In light of the problems highlighted above, the Markov regime-switching model proposed by Hamilton (1989) tend to be the more superficially fair alternative of capturing the latent states. The model assumes the regime procedure follows the Markov chain. The major benefit of the Markov regime-switching model is that it comprises both the dummy variables and threshold models (Fu & Wu, 2020).

This study extends the previous work on herding behaviour by subjecting both the equally and value weighted CSAD to the regime-switching framework which takes cognisance of the autocorrelation, fat tail, volatility clustering and time-varying nature of herding behaviour. Thus, following the approach by Fu and Wu (2020) and Mand and Sifat (2021) the Markov switching model in this study is illustrated as follows:

$$Dispersion_t = \alpha_{0,s_t} + \delta_{1,s_t}|R_{m,t}| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}Dispersion_{t-1} + \sigma_{s_t}\varepsilon_t \quad (3.2)$$

Where: $\varepsilon_t \sim i.i.d.(0,1)$; S_t is a discrete regime indicator taking values in $\{1,2\}$ indicating a 2-state first order, homogenous, irreducible and ergodic Markov chain. This study assumes two (2) state regimes in order to prevent the model from being too complex which often leads to overfitting (Mand & Sifat, 2021). The Markov chain transition probabilities of the specification is as follows:

$$p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\} \quad (3.3)$$

Where: p_{xy} expresses the probability of being in regime x occurring at time $t+1$ provided that the market was in regime y at time t. The transition probabilities above satisfy $\sum_{i=0}^{1} p_{xy} = 1$

3.3.3 Data

Data in this research was obtained from the Namibian Securities Exchange (NSX) for the period 1st January 2003 to 30th June 2023. This sample period is chosen in this study due to availability of data. To avoid survivor bias, all stocks which were listed on the NSX for the period under review are considered in this study including those that have been suspended or delisted. Estimations in this research were done using the Python Statistical Package. It is imperative to note that NSX is an emerging market and thus characterised by thin trading which usually leads to bias in the herding behaviour estimators. As pointed by Pece and Petria (2015) thin trading influences the appearance of non-linear dependencies in the prices of stock thereby leading to a higher level of predictability. Several methods have been proposed in literature to deal with thin trading. Some researchers like Pece and Petria (2015) and Kuttu (2018) followed the approach by Miller *et al*. (1994) which was latter modified by Antoniou *et al*. (1997). Miller *et al.* (1994) point out that a moving average (MA) model that mirrors the number of non-trading days is needed to remove the effect of thin trading. They proved that to get the non-trading adjustment, the moving average (MA) is the same as estimating autoregressive equation of order (1), that is, AR(1). Kuttu (2018) then estimated the AR (1) as follows:

$$r_{it} = \varphi + \beta r_{it-1} + \varepsilon_{it} \tag{3.4}$$

Where: r_{it} measures the daily returns at time t; φ is a constant; r_{it-1} captures the time dependence of the returns series; and ε is the error term which follows $N \sim (0, \sigma^2)$. Kuttu (2018) then utilises the above estimated coefficients and estimated residuals to estimate the adjusted returns as follows:

$$r_{it}^{adj} = \varepsilon_{it}/(1-\beta) \tag{3.5}$$

Where: r_{it}^{adj} is the return at time t adjusted for thin trading.

However, as pointed by Pece and Petria (2015) the criticism of the Miller *et al.* (1994) is the assumption of a constant thin trading adjustment needed to adjust the returns. However, this assumption tends to be valid for highly liquid and developed capital markets and not emerging markets as argued by Antoniou *et al.* (1997). Antoniou *et al.* (1997) then proposed that Equation (3.4) be estimated recursively. However, the above technique do not entirely eliminate the problem of thin trading although it reduces the bias in the beta estimators under thin trades (Brooks *et al.*, 2006). Brooks *et al.* (2006) then proposes selecting most liquid stocks that do not get affected by thin trading in order to get a selectivity corrected beta estimator. The major problem of the approach proposed by Brooks *et al.* (2006) is that t requires selecting only those securities which have traded continuously for the period under review which leads to possibility of survivorship bias as suspended or delisted stocks are dropped from the sample.

Other researchers like Mlambo and Biekpe (2007) utilised the continuous compounded trade-to-trade returns approach in an effort to deal with the issue of thin trading testing for the efficient market hypothesis of the ten African stock markets including the NSX. To obtain the adjustment for interval variability, Mlambo and Biekpe (2007) weighted the trade-to-trade returns by the number of days between trades, that is, interval variability as follows:

$$\tilde{R}_t = \frac{1}{K_t}\left[\ln(P_t) - \ln\left(P_{t-K_t}\right)\right] \tag{3.6}$$

Whereby:

$\tilde{R}_t$ denotes the approximate trade-to-trade returns adjusted for the time interval effect

P_t is the period t closing price

P_{t-K_t} denotes the stock price occurring K_t periods in the past.

K_t denotes the interval length, that is, the time duration between the previous successive trade and period t trade

Despite using the continuous trade-to-trade returns approach, Mlambo and Biekpe (2007) acknowledged that the approach doesn't totally eliminate thin trading (the zero returns) but only reduce them which also a limitation of the trade-to-trade returns approach. Other researchers like Kallinterakis *et al*. (2009) proposed excluding zero returns as a way of dealing with thin trading. The major problem of this approach is that it is based on the assumption that all zero returns are a result of thin trading which is not always the case as some of the zero returns may be as a result of the true generating process of the return (Mlambo *et al.*, 2003).

Some researchers like Škrinjarić (2018) selected the most liquid stock as a way of dealing with thin trading. However, selecting only the most liquid securities may lead to survivorship bias. Furthermore, selecting only the most liquid securities greatly reduces the sample size considering that most developing stock markets like the NSX are still developing and has few securities. Guney *et al.* (2017) utilised value weighted market returns as a way of dealing with thin training. The value weighted market returns are less affected by thin trading as they are shaped by the bigger stocks' returns that are more heavily traded. Thus, the potential of predictability in the herd behaviour estimations is reduced by the use of value weighted market returns. Other researchers like Seetharam and Britten (2013) and Vo and Phan (2017) utilised the long time horizon approach such as the weekly and monthly stock returns as a way of dealing with thin trading. The major thrust of this technique is to increase the chance of the stock having traded during the time period. Furthermore, as pointed by Seetharam and Britten (2013) short time horizon series like the daily data tend to be noisy and provide inaccurate results. The component of insignificant fluctuations in a data series can thus be controlled by utilising low-frequency data like the monthly data series (Seetharam & Britten, 2013).

Despite several proposals, there is no agreement on the best method for dealing with thin trading. This research follows the approach by Seetharam and Britten (2013), Yao *et al.*

(2014) and Vo and Phan (2017) by utilising value weighted monthly stock returns due to the benefits highlighted above.

3.3.4 Unit root tests

Most macroeconomics variables and financial variables are trended. In this regard they tend to be non-stationary. Using non-stationary variables in the regression model leads to spurious results. It is important that before any estimations are done, the variables are tested for unit root. In this research the traditional Augmented Dick Fuller (ADF), Philip Perron (PP) as well as the Dickey-Fuller Generalised Least Square (DF-GLS) championed by Elliott, Rothenberg and Stock (1996) are utilised to test for the for the unit root in the variables. The null hypotheses for ADF, PP and DF-GLS are that there is presence of unit root in the data.

3.3.4.1 The Augmented Dickey Fuller Unit Root Test

One of the widely used test for unit root test is the Dickey and Fuller (DF) unit root test. It is based on the first-order autoregressive process specified as follows:

$$y_t = \theta_1 y_{t-1} + \mu_t, \quad t = 1, \ldots, T \tag{3.7}$$

Where: θ_1 is the parameter of the autoregression and μ_t is the white noise disturbance or error term.

The null and alternative hypotheses are specified as follows:

$H_0: \theta_1 = 1$, the process contains unit root (non-stationary) denoted as I(1)

H_1: $|\theta_1| < 1$, the process doesn't contain unit root (stationary) denoted as I(0)

Subtracting y_{t-1} from both series in equation (3.7) gives the following equation which can be used to calculate the test statistic for the DF Test:

$$\Delta y_t = \beta y_t + \mu_t \tag{3.8}$$

Where: $\beta = \theta_1 - 1$

The test statistic for the DF test is the defined ass as follows:

$$t = \frac{\hat{\theta}_1 - 1}{s_{\hat{\theta}_1}} \tag{3.9}$$

Where: $\hat{\theta}_1$ and $s_{\hat{\theta}_1}$ represents the least square estimate of θ_1 and the standard error estimate respectively.

Expanding Equation (3.7) above by a constant or linear trend gives the following:

$$y_t = \beta_0 + \theta_1 y_{t-1} + \mu_t \tag{3.10}$$

$$y_t = \beta_0 + \beta_1 t + \theta_1 y_{t-1} + \mu_t \tag{3.11}$$

Assuming autocorrelation of the non-systematic component in DF models, the so called Augumented Dickey Fuller test (ADF) can then be constructed. Thus, Equation (3.7) can then be transformed as follows:

$$y_t = \theta_1 y_{t-1} + \sum_{i=1}^{p=1} y_i \Delta y_{t-1} + \mu_t \tag{3.12}$$

To calculate the test statistic of the DF test, the following equation is then utilised:

$$y_t = (\theta_1 - 1)y_{t-1} + \sum_{i=1}^{p=1} y_i \Delta y_{t-1} + \mu_t \qquad (3.13)$$

One of the biggest practical problems for the implementation of the ADF test is the choice of the lags p. The maximum lag $p_{max} = 12(T/100)^{1/4}$ should then be chosen as suggested by Schwert (1989). It is imperative to note that a too low p usually leads to autocorrelation and a too larger p leads to lower power of the test. A constant or linear trend can also be used to expand Equation (3.12) above. The following equation can then be used for tests:

$$y_t = d_t + \theta_1 y_{t-1} + \sum_{i=1}^{p=1} y_i \Delta y_{t-1} + \mu_t \qquad (3.14)$$

Where: $d_t = 1 + \sum_{i=0}^{p} \beta_i t^i$

3.3.4.2 Phillips-Perron (PP) Test

As note in the ADF test the selection of lag p is usually a problem due to autocorrelation and heteroskedastic non-system component in the time series. In order to deal with this issue of serial correlation and heteroskedastic, Phillips and Perron (1988) modified the test statistics of the standard DF test with non-parametrically test statistics. The PP Test is also grounded on the Equation (3.7), (3.10) and (3.11). However, a central time variable is used to replace the linear trend in Equation (3.11). Instead of using differential equations in the calculation of the test statistics, it is directly derived from Equation (3.7), (3.10) and (3.11). According to Pesaran (2015) and Arltová and Fedorová (2016) the Z test statistics with constant are specified as follows:

$$Z_{\theta} = T(\hat{\theta}_T - 1) - \frac{1}{2}\frac{T^2 s_{\hat{\theta}}^2}{s_T^2}(s_{LT}^2 - s_T^2) \quad (3.15)$$

$$Z_T = \left(\frac{s_T}{s_{LT}}\right) t_{DF} - \frac{1}{2}(s_{LT}^2 - s_T^2)\frac{1}{s_{LT}}\frac{T s_{\hat{\theta}}}{s_T} \quad (3.16)$$

Where:

$t_{DF} = \frac{\hat{\theta}_T - 1}{s_{\hat{\theta}}}$, is the DF test statistics

$s_T^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t^2$, is the non-systematic component variance's OLS estimator

$s_{LT}^2 = s_T^2 + 2\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\hat{y}_{j,T}$, in which q is the covariates' number of lags and

$\hat{y}_{j,T} = \frac{1}{T}\sum_{t=j+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-j}$ is the non-systematic component variance's maximum likelihood estimator

The non-autocorrelation of the error term implies $\hat{y}_{j,T} = 0$, for $j > 0$, and $s_{LT}^2 = s_T^2$. In this regard the t-statistics test is independent of the autoregressive of the error term process. Ultimately the Z test statistics are reduced to DF test statistics which point to the fact that DF test is just a special case of non-parametric tests.

3.3.4.3 ADF-GLS

This unit root test is sometimes known as the Elliot-Rothenberg (ERS) Test (Elliott *et al.*, 1996). As a modification of the ADF Test, the ADF-GLS uses the detrending transformation prior to testing for unit root. Based on the general least squares method (GLS) the constant in Equation (3.10) is estimated using the following transformation:

$$\begin{matrix} \tilde{y}_1 = y_{1,} \tilde{y}_t = y_t - \varphi y_{t-1} & t = 2, \dots, T, \\ x_1 = 1, x_t = 1 - \varphi & , \; t = 2, \dots, T, \end{matrix} \qquad (3.17)$$

Where: $\varphi = 1 + \bar{c}/T$ and $\bar{c} = -7,$ based on the following model:

$$\tilde{y}_t = \alpha_0 x_t + \mu_t \qquad (3.18)$$

The constant from time series y_t is then removed by estimating $\tilde{\alpha}_0$ utilising the least squares methods as follows:

$$y_t^* = y_t - \hat{\alpha}_0 \qquad (3.19)$$

As the final step, the following transformed time series model is then used in the calculation of the ADF test:

$$\Delta y_t^* = \theta_1 y_{t-1}^* + \sum_{i=1}^{p} y_i \Delta y_{t-i}^* + \mu_t \qquad (3.20)$$

The GLS is used to estimate the trend in equations with linear trend. Thus, Equation (3.16) is then extended by $z_1 = 1,\; z_t = t - \varphi(t-1)$, whereby $\varphi = 1 + \bar{c}/T$ and $\bar{c} = -13.5$. The following equation is then used to estimate the parameters:

$$\tilde{y}_t = \alpha_0 x_t + \beta_1 z_t + \mu_t \qquad (3.21)$$

The trend from the time series y_t is then removed by estimating the parameters $\hat{\alpha}_0$ and $\hat{\beta}_1$ as follows:

$$y_t^* = y_t - (\hat{\alpha}_0 + \hat{\beta}_1 t) \tag{3.22}$$

Lastly, the following equation can then be used to obtain the test statistic for the ADF test:

$$\Delta y_t^* = \alpha_0 + \theta_1 y_{t-1}^* + \sum_{i=1}^{p} y_i \Delta y_{t-i}^* + \mu_t \tag{3.23}$$

3.3.4.4 Zivot and Andrews Unit Root Test

The conventional unit root tests such as ADF, PP and DF-GLS are often criticised for not allowing for possibility of structural break points in the data series, ultimately leading to spurious and biased results (Bala Umar *et al.*, 2015). Perron (1989) noted that if time of the break is assumed as an exogenous occurrence, in the instance of true stationary alternative and ignored structural break, the power to reject a unit root then dwindles. By assuming an unknown exact time of the break point, Zivot-Andrews then recommends a variation of Perron's initial test. As a proxy for Perron's idiosyncratic procedure in determining the break-point, a data dependent algorithm is used instead. In this regard, to determine the break-points, data dependent algorithm is used. Perron (1989) disclosed that to test for the unit root with the existence of a structural break, Zivot and Andrews (1992) developed the following three (3) models:

i. Model (A) : permits a one-time change in the in the level of the series

ii. Model (B): allows for a one-time change in the trend function's slope

iii. Model (C): permits one-time changes in both the level and the slope of the trend function.

The corresponding regressions equations to the above three (3) models is specified as follows:

Model A: $\Delta z_t = c + \theta z_{t-1} + \beta_t + \delta DU_t + \sum_{j=i}^{k} d_j \Delta z_{t-j} + \mu_t$ (3.24)

Model B: $\Delta z_t = c + \theta z_{t-1} + \beta_t + \gamma DT_t + \sum_{j=i}^{k} d_j \Delta z_{t-j} + \mu_t$ (3.25)

Model C: $\Delta z_t = c + \theta z_{t-1} + \beta_t + \gamma DU_t + \delta DT_t + \sum_{j=i}^{k} d_j \Delta z_{t-j} + \mu_t$ (3.26)

Where: DU_t is a dummy variable indicating a mean shift occurring at each break-point time (TB) while the trend shift variable is denoted by DT_t. Thus,

$DU_t = \begin{Bmatrix} 1 \dots .. if\ t > TB \\ 0 \dots .. if\ t < TB \end{Bmatrix}$; and

$DT_t = \begin{Bmatrix} t - TB \dots .. if\ t > TB \\ 0 \dots \dots \dots .. if\ t < TB \end{Bmatrix}$

The null hypothesis of the above models is $\theta = 0$ implying non-stationery series with a drift that disregards any structural breakpoint. Contrariwise, $\theta < 0$ hypothesis entails trend-stationary series with one (1) unknown breakpoint time. Under Zivot and Andrews every point is regarded as possible break point. As a result a regression is run sequentially for every possible time break (TB). The TB that minimises or decreases one-sided t-statistics testing $\hat{\theta}(= \theta - 1) = 1$ is then chosen from all the possible break points (TB). Zivots and Andrews asserts that the presents of endpoints leads to asymptotic distribution of the statistics that is deviated towards infinity. Thus, selection of some regions where the endpoints of the sample are not included is required. Zivot and Andrews advocated for trimming regions which is specified as (0.15T, 0.8T). As argued by Perron (1997) using either Model A or 3 can adequately model most economic time series. Thus, Model A and/or Model has been frequently used in most researches. Sen (2003) noted that substantive loss in power will occur if one applies Model A in the situation when a break happens in Model C. However, the loss of power is minor if Model C is used when the break is actually a Model A phenomenon. All these arguments point to the superiority of Model C over Model A. Thus, the Model C for the Zivot and Andrews unit root test is preferred in this study.

3.3.5 Brock-Dechert-Scheinkman-LeBaron test for linearity in the data series

Broock *et al*. (1996) developed a non-parametric widely known as the BDS test to detect nonlinear serial dependence in the data series. It was developed to detect hidden patterns in stochastic data series. The null hypothesis of this test is that the data series is independently and identically distributed (iid). The correlation integral is the cornerstone of the BDS test. It is the measure by which the temporal patterns are repeated in the time series. Given a time series x_t for $t = 1,2 \dots, T$ and m dimensional vectors or histories, $x_t^m = (x_t, x_{t+1}, \dots, x_{t+m-1})$, the correlation integral at embedding dimensions m can thus be estimated as:

$$C_{m,T}(\in) = \frac{2}{T_m(T_{m-1}))} \sum_{t=1}^{T_{m-1}} \sum_{s=t+1}^{T_m} I_{\in}(x_t^m, x_s^m) \qquad (3.27)$$

Whereby: $T_m = T - m + 1$, and $I(x_t^m, x_s^m; \in)$ is an indicator function of the occasion

$$\|x_t^m - x_s^m\| = \max_{i=0,1,\ldots m-1} |x_{t+1} - x_{s+1}| < \in \quad (3.28)$$

The BDS statistics for data series of length T is then specified as follows:

$$\text{BDS}_{m,T}(\in) = \sqrt{T}\,\frac{C_{m,T}(\in) - C_{1,T}(\in)^m}{\sigma_{m,T}(\in)} \quad (3.29)$$

Whereby: T denotes the size of the sample; $\in$ denotes a randomly selected proximity parameter and $\sigma_{m,T}(\in)$ denotes the standard deviation of $\sqrt{T}(C_{m,T}(\in) - C_{1,T}(\in)^m)$ which can be estimated as documented by Broock *et al.* (1996). Assuming a fairly reasonable regulatory circumstances, the BDS test statistics converges to a normal distribution $N(0,1)$:

$$\text{BDS}_{m,T}(\in) \xrightarrow{d} N(0,1) \quad (3.30)$$

Thus, the null hypothesis of independently and identically distributed (iid) is rejected whenever $\left|\text{BDS}_{m,T}(\in)\right| > 1.96$

3.4 Results and discussions

3.4.1 Descriptive statistics

Table 3.2 and Table 3.3 below presents the descriptive statistics for all the variables using both the weekly and monthly data.

Table 3.2: Descriptive statistics of the weekly equally and value weighted variables for the NSX covering the period 01 January 2003 to 30 June 2023

	Equally weighted weekly data			**Value weighted weekly data**		
Statistical analysis	CSAD	MKT	MKT2	CSADWGHT	MKTWGHT	MKT2WGHT
Mean	1.023475	0.032016	0.4374372	0.055774	0.001109	0.001824694
Median	0.898194	0.051923	0.1065225	0.045118	0.002088	0.000497834
Minimum	0.194614	-3.581071	0.0000001	0.007087	-0.215789	0.000000001
Maximum	7.242207	4.057848	16.46613	0.346224	0.217853	0.04745994
Standard Deviation	0.620639	0.660922	1.191666	0.042099	0.042722	0.00471125
Kurtosis	26.349669	5.475895	66.261022	9.938834	4.712774	48.11641
Skewness	3.975312	-0.026308	7.106116	2.627949	-0.182104	6.341523
Jarque-Bera	33684.34***	1330.5***	204207.9***	5623.01***	991.05***	110107.4***
Observation	1077	1077	1077	1077	1077	1077
ACF1	0.315	-0.016	0.248	0.382	-0.032	0.327
ACF2	0.154	-0.07	0.127	0.353	-0.119	0.290
ACF5	0.113	0.003	0.002	0.291	0.007	0.227
ACF10	0.091	-0.033	0.045	0.247	-0.020	0.136
ACF20	0.104	0.085	0.067	0.177	0.063	0.149

Notes: The auto correlation with n as the number of lags is computed by AFC_n . *** denotes significance at 1 % level of significance

Table 3.3: Descriptive statistics of the monthly equally and value weighted variables for the NSX covering the period 01 January 2003 to 30 June 2023

	Equally weighted monthly data			**Value weighted monthly data**		
Statistical analysis	CSAD	MKT	MKT2	CSADWGHT	MKTWGHT	MKT2WGHT
Mean	2.448206	0.128630	2.242078	0.117724	0.007774	0.006320179
Median	2.196615	0.186458	0.818786	0.099414	0.010699	0.002357345
Minimum	1.063899	-7.579272	0.000146	0.023445	-0.317904	0.000000046
Maximum	8.291388	5.684741	57.445367	0.489232	0.253923	0.1010629
Standard Deviation	1.162729	1.494863	5.302623	0.070055	0.079280	0.01211047
Kurtosis	7.834047	3.911853	55.978636	7.0074	1.965346	25.665833
Skewness	2.50435	-0.537898	6.586746	2.192235	-0.543386	4.531705
Jarque-Bera	854.1***	160.3***	32564.1***	674.4***	49.0***	7301.1***
Observation	246	246	246	246	246	246
ACF1	0.364	0.041	0.149	0.169	-0.058	0.275
ACF2	0.102	0.021	-0.025	0.196	0.010	0.046
ACF5	0.060	0.029	-0.005	0.155	0.013	0.197
ACF10	0.227	0.044	0.043	0.028	-0.059	-0.008
ACF20	0.09	-0.027	-0.055	0.099	0.045	0.003

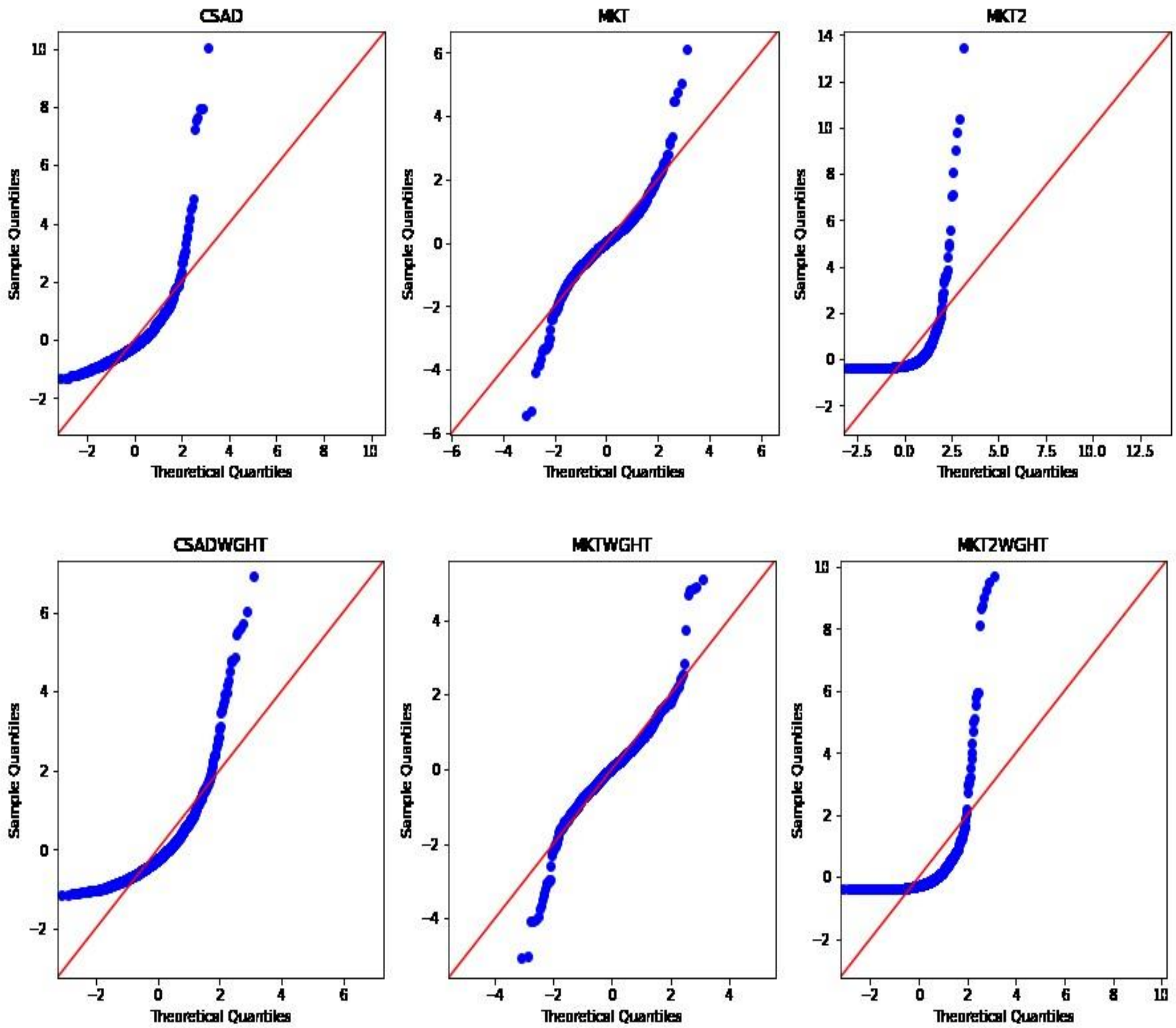
Notes: The auto correlation with n as the number of lags is computed by AFC_n . *** denotes significance at 1 % level of significance

From Table 3.2 and Table 3.3 above, it can be observed that all other variables are strictly positive, while the weekly and monthly equally (MKT) and value (MKTWGHT) weighted market returns takes negative values indicating more great downwards than upturn movements. However, the means of the MKT and MKTWGHT are positive for the period under review which may point to the better performance of the Namibian Securities Exchange (NSX). The equally weighted average weekly and monthly market returns of the NSX over the period are 3.20% and 12.86 % respectively while the value weighted average weekly and monthly market returns are 0.11% and 0.77% . The mean values of the equally weighted cross-section standard deviations (CSAD) is greater than the mean values of the value weighted cross-section standard deviations (CSADWGHT) which may suggest that the dispersions of the weekly and monthly market returns are more likely to be pronounced in the smaller stocks than larger once. Furthermore, the means and medians of all the variables exhibits consistency as they all fall within their minimum and maximum values.

The NSX also exhibits a relatively lower level of volatility of the weekly and monthly market returns as evidenced by the low standard deviation of 0.66 and 1.49 respectively for the equally weighed market returns as well as 0.042 and 0.079 respectively for the weekly and monthly value weighted market returns. The data also exhibits higher level of leptokurtosis for most variables as evidenced by higher values of skewness and kurtosis greater than 3. As pointed by Wegner (2007), the decision of rule of thumb is that marginal skewness is present when the coefficient which lies between -0.5 and +0.5 while moderate skewness is present when the coefficient value is between -1 and +1. Lastly the excessive skewness is present when the coefficient values lies outside the range <-1 and >+1. From the results in Table 3.2 and Table 3.3 above, both the equally and value weighted weekly and monthly market returns are close to normal distribution but marginally skewed to the left . There is marginal skewness in the weekly and monthly market returns which implies a few high valued outliers. There is excessive skewness in both equally (MKT) and value weighted (MKT2) squared of the market returns. The excessive skewness may be attributed to the larger sample size.

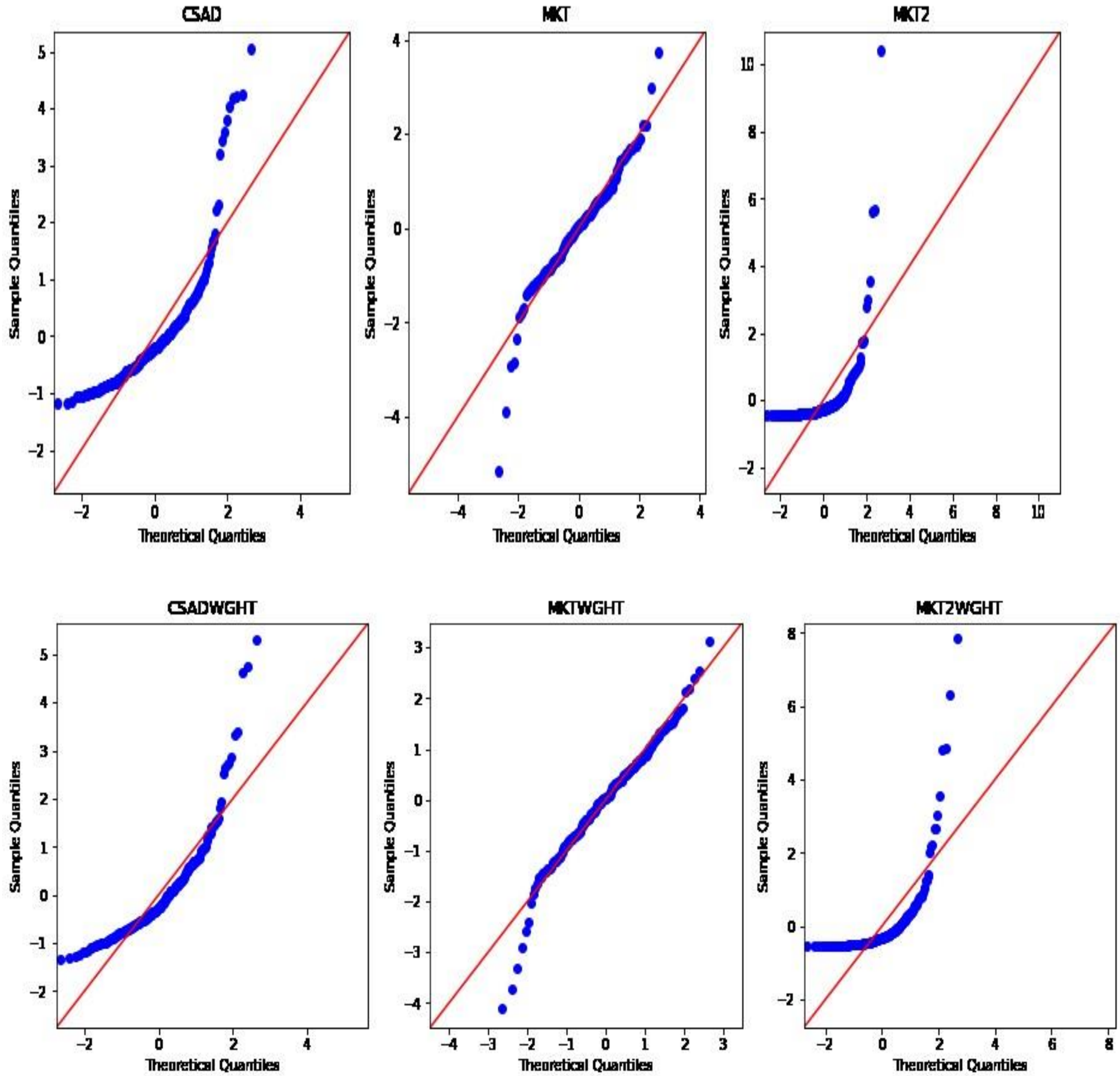
All the variables exhibit fat tails as evidenced by the positive excess kurtosis. Apart from this, the results of the Jarque-Bera test indicate that we reject the null hypothesis of normality at 1% level of significant and conclude that the residual distributions of all these variables are non-normal. Furthermore, a closer inspection of the Quantile-Quantile (Q-Q) plots in Figure 3.1 and Figure 3.2 below shows that not all points lie on the normal distribution line which also suggests non-normality of the variables used in this study. Thus, the non-normality distribution of the data also supports the preference of CSAD in this study over CSSD following the approach by Chang *et al.* (2000) and also the preference of the MRSM approach over the OLS method. Figure 3.3 and Figure 3.4 below shows the volatility clustering of the variables as high changes are followed by some high changes or low changes followed by low changes. The volatility clustering of the CSAD and CSADWGHT seem to be closely related to that of MKT and MKTWGHT respectively under both the weekly and monthly scenarios. Furthermore, the MRSM is very good at apprehending fat tails, volatility clustering and robust autocorrelation characteristics in a data series.

Figure 3.1: QQ plots for the weekly variables for NSX covering the period 01/01/03-30/06/23



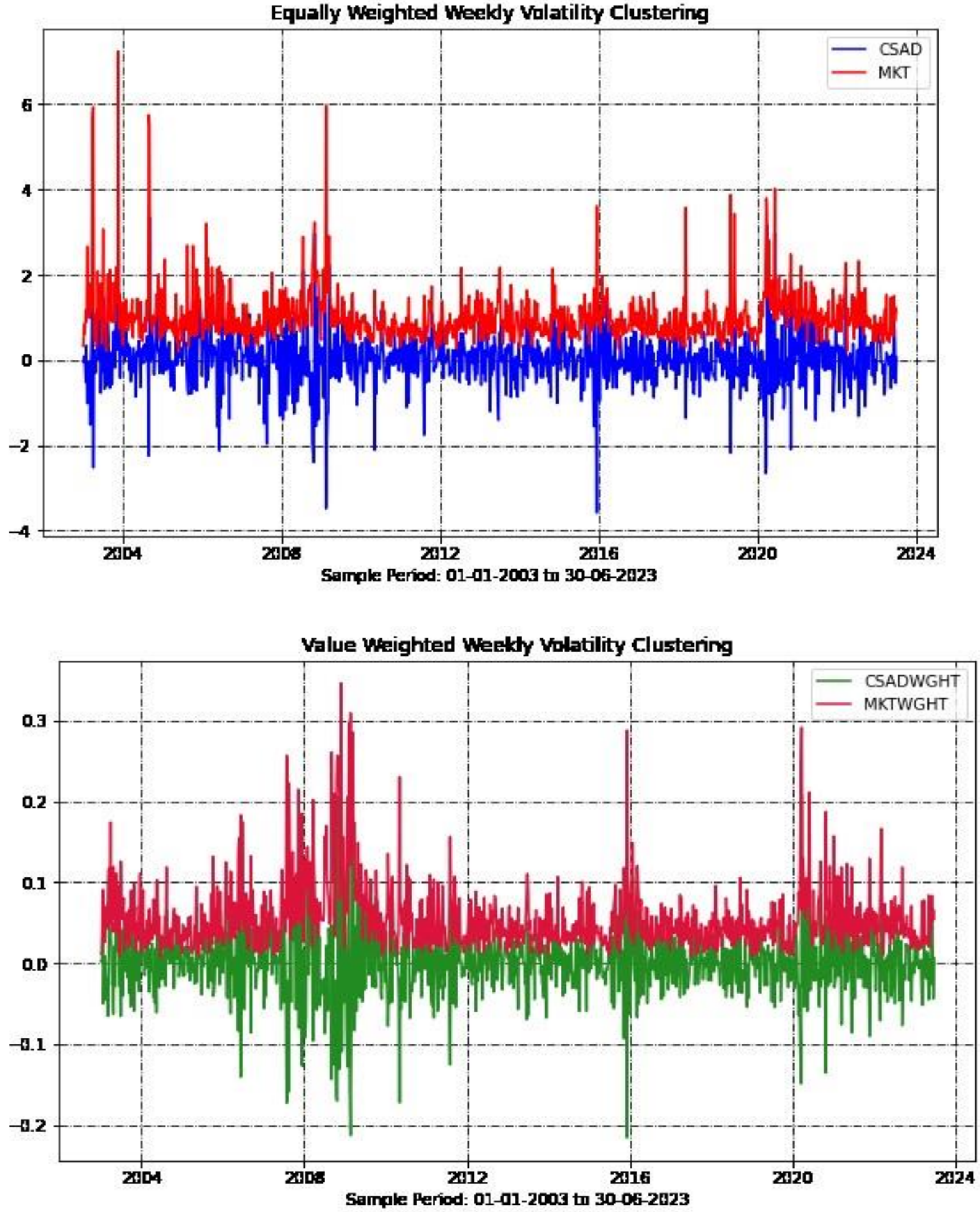
Source: Python results (2024)

Figure 3.2: QQ plots for the monthly variables for NSX covering the period 01/01/03-30/06/23



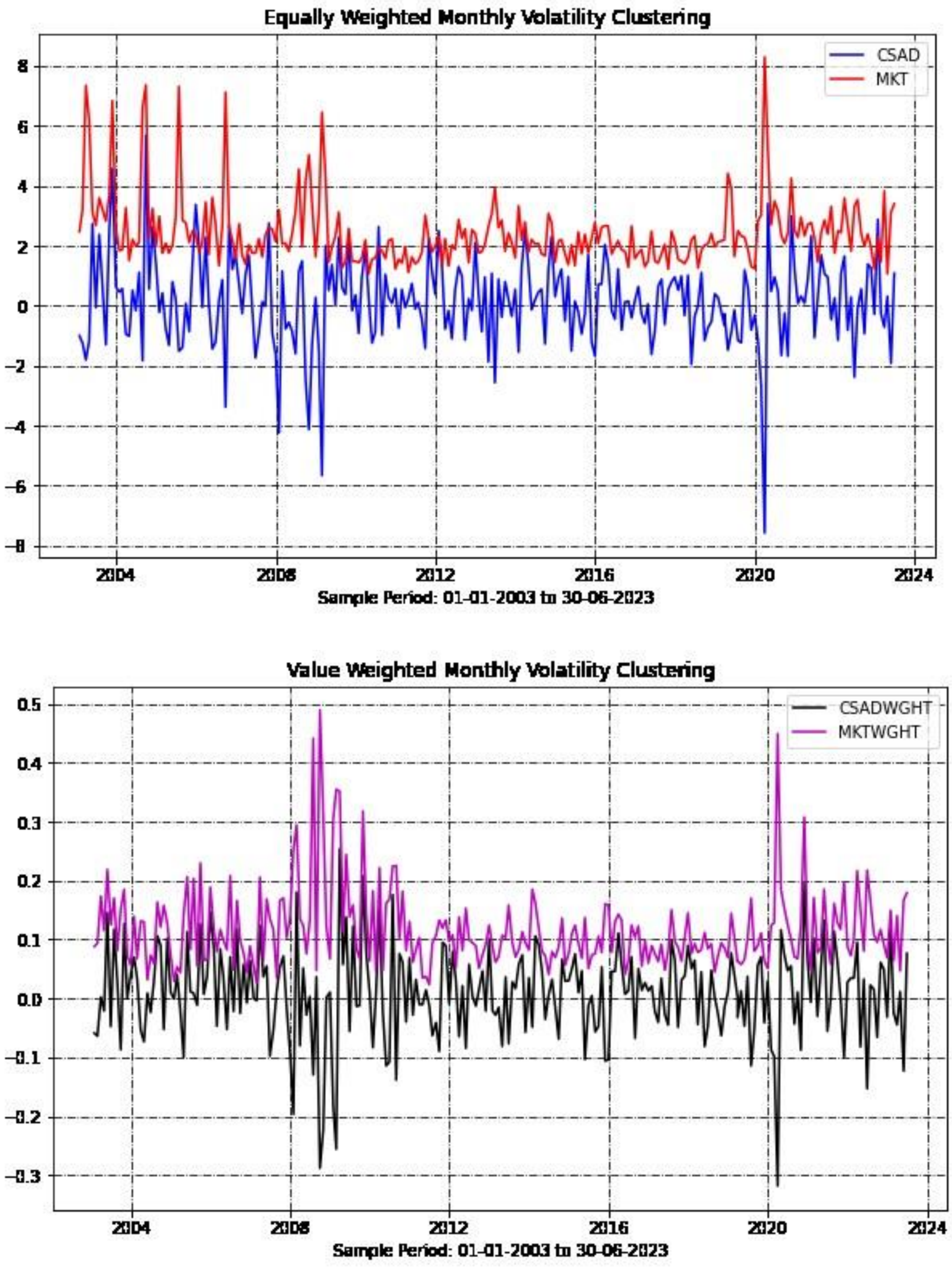
Source: Python results (2024)

Figure 3.3: Volatility clustering of the weekly variables covering the period 01/01/03-30/06/23



Source: Python results (2024)

Figure 3.4: Volatility clustering of the monthly variables covering the period 01/01/03-30/06/23

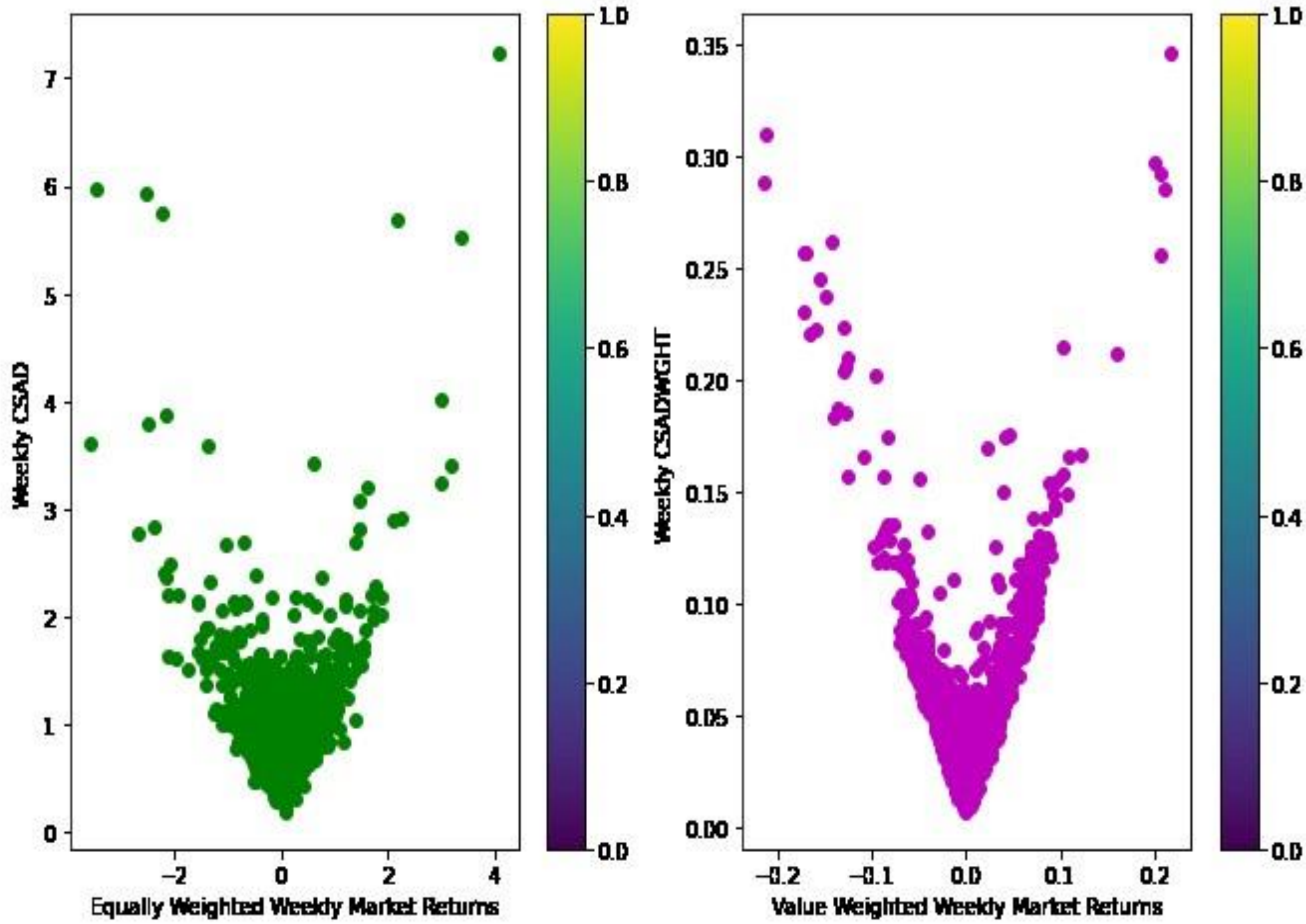


Source: Python results (2024)

Figure 3.5 and Figure 3.6 below provides an insight on the non-linearity of the relationship between stock market returns and the stock returns dispersion for the period 01 January 2003 to 30th June 2023. A positive and linear relationship is expected under the rational asset pricing models. Figure 3.5 and Figure 3.6 show that the relationship is not that linear. It can be observed that the equally and value weighted cross-section standard deviations tends to be narrower as the stock market returns surpasses a certain threshold. This supports the notion by Christie and Huang (1995) that herding behaviour is prevalent during market abnormal conditions (market stress conditions).However, the value weighted market returns exhibits a more linear relationship as compared to the equally weighted returns.

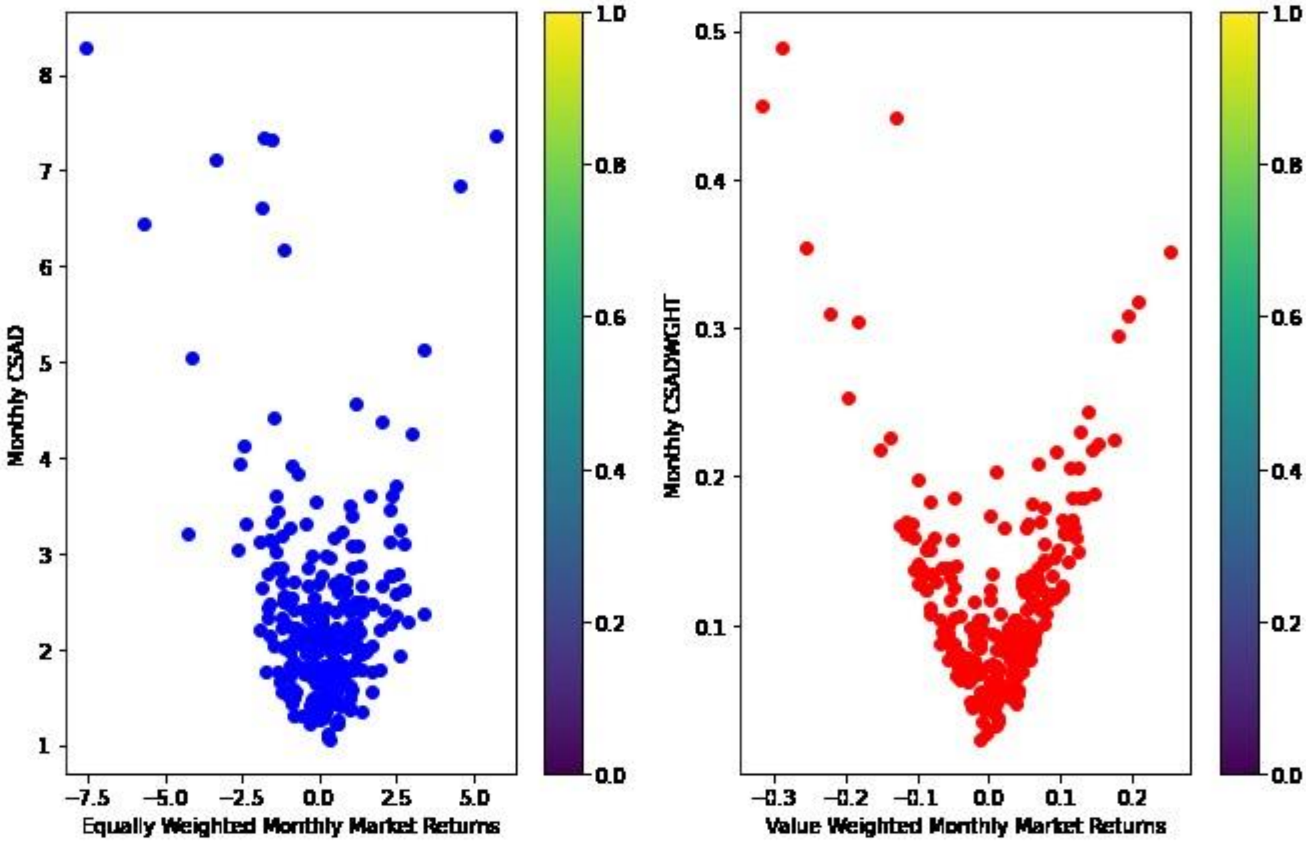
The Pearson correlation results in Figure 3.3 shows there is extremely weak relationship between CSAD and the market returns under both the equally and value weighted approach which is in line with Chang *et al.* (2000) prediction of non-linearity relationship between these two variables. The correlation analysis tells us the strength of the relationship between two variables and not the predictive power. Thus no conclusive decision about the relationship can be reached without regression results.

Figure 3.5: Plots of the weekly CSAD and CSADWGHT against the equally weighted market returns (MKT) and value weighted market returns (MKTWGHT) respectively



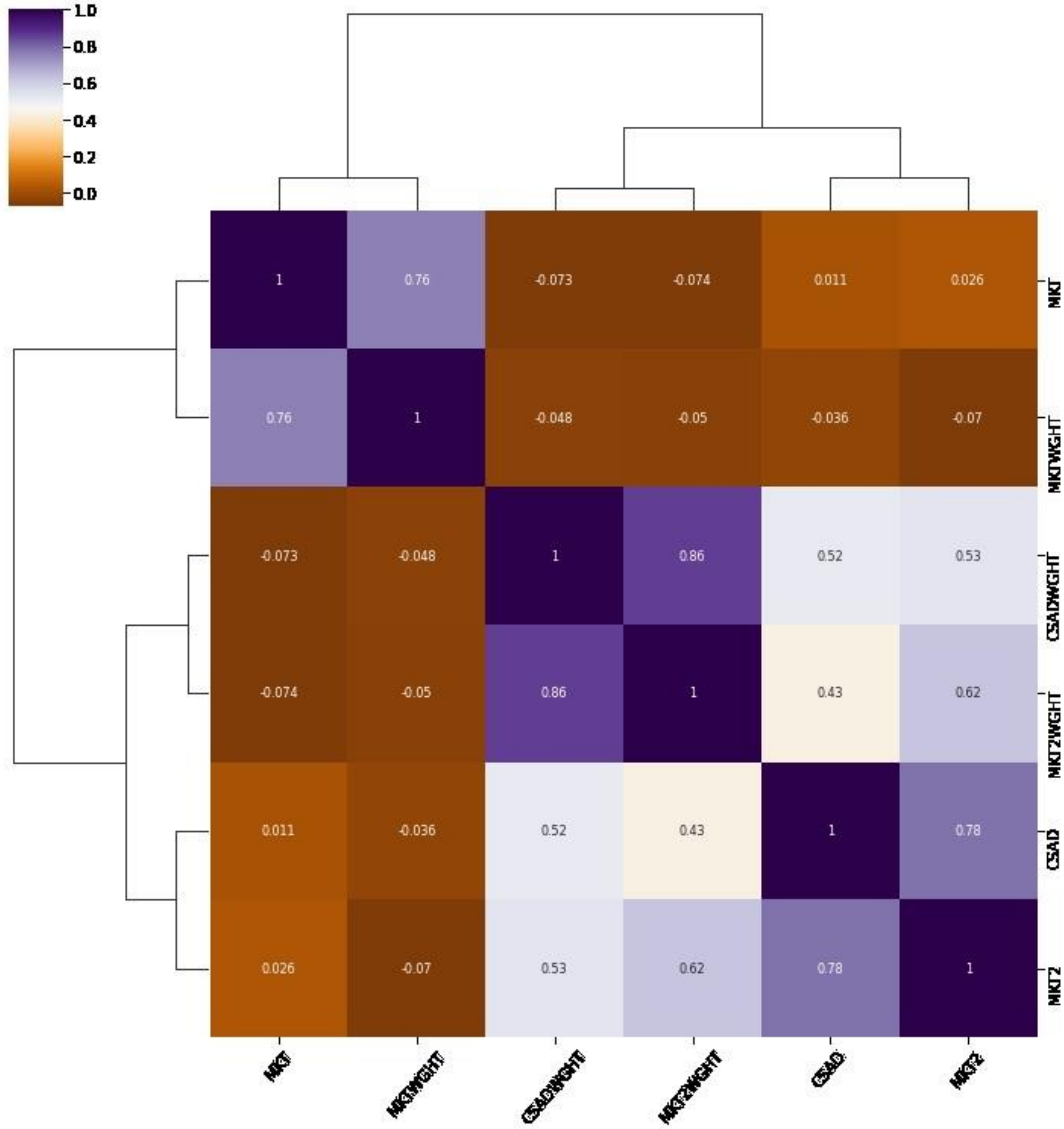
Source: Python results (2024)

Figure 3.6: Plots of the monthly CSAD and CSADWGHT against the equally weighted market returns (MKT) and value weighted market returns (MKTWGHT) respectively



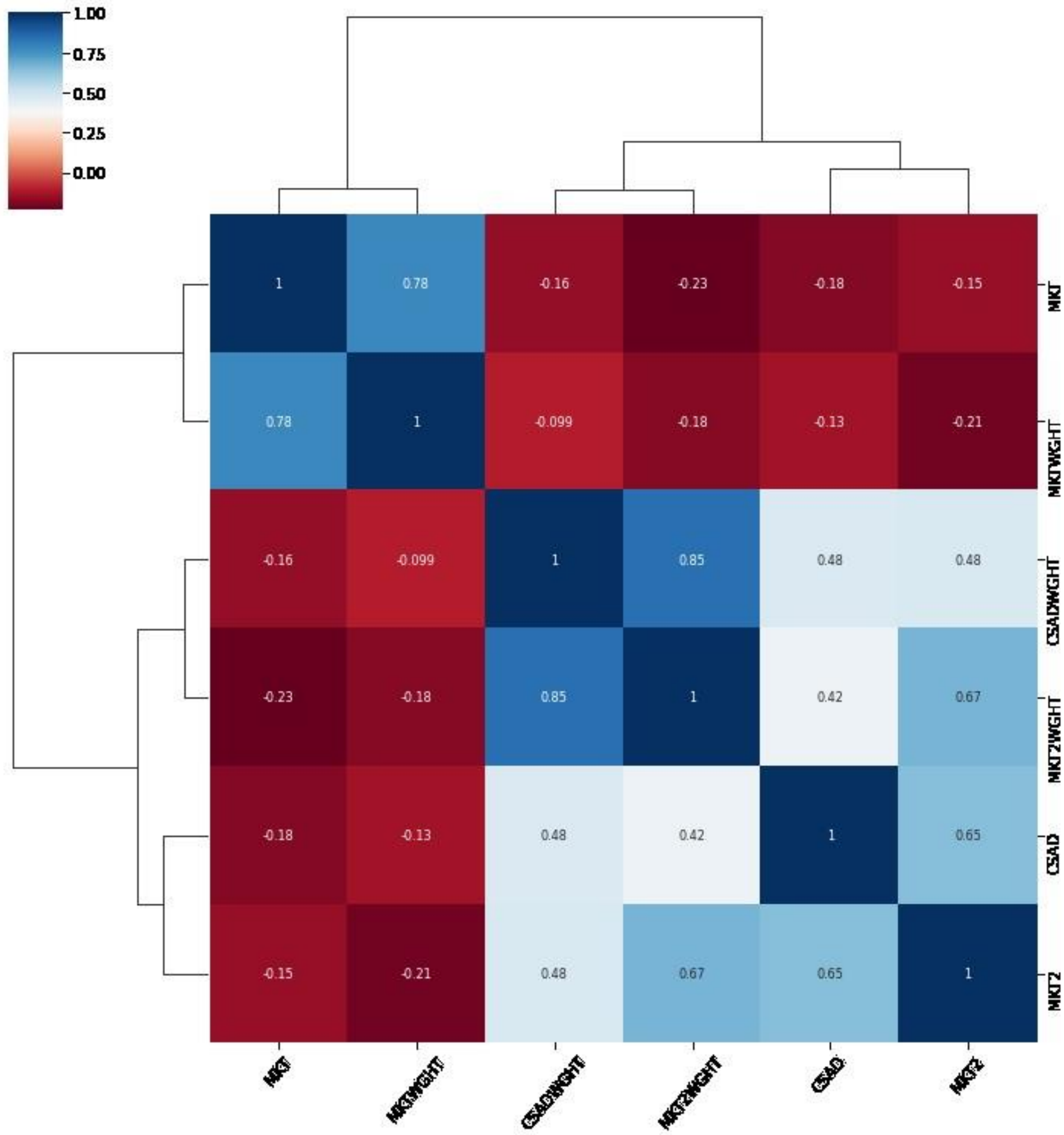
Source: Python results (2024)

Figure 3.7: Correlation matrices of the variables using weekly data



Source: Python results (2024)

Figure 3.8: Correlation matrices of the variables using monthly data



Source: Python results (2024)

3.4.2 Unit root test results

Before regression equations are done in this research, variables are tested for unit root to ensure that they don't suffer from non-stationarity. As highlighted in the methodology section, most financial time data series are trended and therefore tend to be non-stationary. The use of non-stationary variables in regression equations often leads to spurious results. .The results of the conventional unit root tests ADF, PP and DF-GLS are shown in Table 3.4 and Table 3.5 below. The ADF, PP and DF-GLS unit root results indicate that equally weighted market returns (MKT), absolute standard deviation (CSAD) and the squared of the market returns (MKT2) are stationary at levels for both the weekly and monthly data. Furthermore, the value weighted market returns (MKTWGHT), absolute standard deviation (CSADWGHT) and the squared of the market returns (MKT2WGHT) are stationary at levels for both weekly and monthly data. The results of the unit root test in this study also corroborates with findings by other researchers like Yao *et al.* (2014) and Škrinjarić (2018). This indicates that the regression can be estimated with no fear of obtaining spurious results. To ensure consistency the Zivot-Andrews unit root tests are compared to the conventional unit root tests above. The Zivot-Andrews unit root tests results are presented in Table 3.6 and Table 3.7. As highlighted in the methodology section, results of the of Model C (Equation 3.26) indicate that we reject the null hypothesis of unit root at 5% significance level and conclude that all the variables are stationary in levels which is in line with the results obtained from the ADF, PP and DF-GLS unit root tests.

Table 3.4: Unit root test results for the monthly variables using ADF, PP and DF-GLS

		Monthly Data		
		ADF	Phillip-Perron	DF-GLS
Variable		Levels	Levels	Levels
CSAD	Constant	-10.604 (-2.873)**	-11.690 (-2.87)**	-2.455 (-2.03)**
	Constant & Trend	-10.778 (-3.428)**	-11.774 (-3.43)**	-3.385 (-2.93)**
MKT	Constant	-14.961 (-2.873)**	-15.005 (-2.87)**	-11.499 (-2.03)**
	Constant & Trend	-14.988 (-3.428)**	-15.002 (-3.43)**	-13.379 (-2.93)**
MKT2	Constant	-13.407 (-2.873)**	-13.386 (-2.87)**	-13.010 (-2.03)**
	Constant & Trend	-13.471 (-3.428)**	-13.388 (-3.43)**	-13.227 (-2.93)**
CSADWGHT	Constant	-8.364 (-2.873)**	-15.471 (-2.87)**	-2.711 (-2.03)**
	Constant & Trend	-8.438 (-3.428)**	-15.443 (-3.43)**	-2.944 (-2.93)**
MKTWGHT	Constant	-16.522 (-2.873)**	-16.515 (-2.87)**	-11.861 (-2.03)**
	Constant & Trend	-16.513 (-3.428)**	-16.515 (-3.43)**	-14.397 (-2.93)**
MKT2WGHT	Constant	-11.753 (-2.873)**	-13.006 (-2.87)**	-2.987 (-2.03)**
	Constant & Trend	-11.770 (-3.428)**	-12.969 (-3.43)**	-3.108 (-2.93)**

Note: The numbers in parentheses are the critical values at the 5% level of significance.

Table 3.5: Unit root test results for the weekly variables using ADF, PP and DF-GLS

		Weekly Data		
		ADF	Phillip-Perron	DF-GLS
Variable		Levels	Levels	Levels
CSAD	Constant	-18.015 (-2.864)**	-28.238 (-2.86)**	-2.653 (-1.96)**
	Constant & Trend	-18.144 (-3.414)**	-28.168 (-3.41)**	-3.286 (-2.87)**
MKT	Constant	-25.142 (-2.864)**	-33.363 (-2.86)**	-15.314 (-1.96)**
	Constant & Trend	-25.219 (-3.414)**	-33.492 (-3.41)**	-15.444 (-2.87)**
MKT2	Constant	-18.720 (-2.864)**	-27.428 (-2.86)**	-12.910 (-1.96)**
	Constant & Trend	-18.795 (-3.414)**	-27.340 (-3.41)**	-13.933 (-2.87)**
CSADWGHT	Constant	-14.233 (-2.864)**	-30.958 (-2.86)**	-2.073 (-1.96)**
	Constant & Trend	-14.435 (-3.414)**	-31.017 (-3.41)**	-2.945 (-2.87)**
MKTWGHT	Constant	-26.545 (-2.864)**	-33.987 (-2.86)**	-9.842 (-1.96)**
	Constant & Trend	-26.533 (-3.414)**	-33.973 (-3.41)**	-9.861 (-2.87)**
MKT2WGHT	Constant	-15.415 (-2.864)**	-30.213 (-2.86)**	-3.622 (-1.96)**
	Constant & Trend	-15.498 (-3.414)**	-30.168 (-3.41)**	-4.071 (-2.87)**

Note: The numbers in parentheses are the critical values at the 5% level of significance.

Table 3.6: Unit root test results for the monthly variables using Zivot-Andrews one break unit root test

		Monthly Data	
		Levels	
Variable		[k]	t-statistics
CSAD	Intercept	[1]	-6.649 (-4.81)**
	Trend	[1]	-6.407 (-4.41)**
	Both	[1]	-6.800 (-5.07)**
MKT	Intercept	[1]	-15.231 (-4.81)**
	Trend	[1]	-15.065 (-4.41)**
	Both	[1]	-15.690 (-5.07)**
MKT2	Intercept	[1]	-13.912 (-4.81)**
	Trend	[1]	-13.610 (-4.41)**
	Both	[1]	-14.417 (-5.07)**
CSADWGHT	Intercept	[1]	-5.607 (-4.81)**
	Trend	[1]	-4.578 (-4.41)**
	Both	[1]	-5.198 (-5.07)**
MKTWGHT	Intercept	[1]	-16.830 (-4.81)**
	Trend	[1]	-16.612 (-4.41)**
	Both	[1]	-17.250 (-5.07)**
MKT2WGHT	Intercept	[1]	-5.661 (-4.81)**
	Trend	[1]	-4.977 (-4.41)**
	Both	[1]	-6.232 (-5.07)**

Note: The numbers in parentheses are the critical values at the 5% level of significance.

Table 3.7: Unit root test results for the weekly variables using Zivot-Andrews one break unit root test

		Weekly Data	
		Levels	
Variable		[k]	t-statistics
CSAD	Intercept	[1]	-10.975 (-4.81)**
	Trend	[1]	-10.646 (-4.41)**
	Both	[1]	-11.456 (-5.07)**
MKT	Intercept	[1]	-15.982 (-4.81)**
	Trend	[1]	-15.888 (-4.41)**
	Both	[1]	-16.192 (-5.07)**
MKT2	Intercept	[1]	-15.257 (-4.81)**
	Trend	[1]	-14.981 (-4.41)**
	Both	[1]	-15.574 (-5.07)**
CSADWGHT	Intercept	[1]	-8.282 (-4.81)**
	Trend	[1]	-7.856 (-4.41)**
	Both	[1]	-6.240 (-5.07)**
MKTWGHT	Intercept	[1]	-10.181 (-4.81)**
	Trend	[1]	-4.276 (-4.41)**
	Both	[1]	-10.590 (-5.07)**
MKT2WGHT	Intercept	[1]	-9.613 (-4.81)**
	Trend	[1]	-9.453 (-4.41)**
	Both	[1]	-10.936 (-5.07)**

Note: The numbers in parentheses are the critical values at the 5% level of significance

3.4.3 Brock-Dechert-Scheinkman (BDS) test results for linearity

The results of the BDS test for linearity in Table 3.8 below reveal that we reject the null hypothesis that the data series is linearly dependent for all the variables and conclude that it is nonlinear which validates the use of the Markov Regime Switching models in this research.

Table 3.8: Results of Brock-Dechert-Scheinkman (BDS) test for linearity

Embedding dimension (Weekly data)									Conclusion
	2		3		4		5		
Variable	Statistics	Probability	Statistics	Probability	Statistics	Probability	Statistics	Probability	
CSAD	7.15	0.0000	8.15	0.0000	8.50	0.0000	8.94	0.0000	Nonlinear
MKT	7.71	0.0000	7.64	0.0000	8.29	0.0000	8.50	0.0000	Nonlinear
MKT2	6.05	0.0000	5.40	0.0000	5.82	0.0000	6.00	0.0000	Nonlinear
CSADWGHT	9.75	0.0000	11.73	0.0000	12.14	0.0000	12.38	0.0000	Nonlinear
MKTWGHT	10.31	0.0000	12.21	0.0000	13.18	0.0000	13.65	0.0000	Nonlinear
MKT2WGHT	8.89	0.0000	9.75	0.0000	10.32	0.0000	10.25	0.0000	Nonlinear
Embedding dimension (Monthly data)									Conclusion
	2		3		4		5		
Variable	Statistics	Probability	Statistics	Probability	Statistics	Probability	Statistics	Probability	
CSAD	5.32	0.0000	5.79	0.0000	5.45	0.0000	5.11	0.0000	Nonlinear
MKT	2.86	0.0041	2.51	0.0119	2.09	0.0363	2.21	0.0265	Nonlinear
MKT2	1.85	0.0063	1.87	0.0060	2.25	0.0239	3.80	0.0001	Nonlinear
CSADWGHT	3.06	0.0022	3.74	0.0001	4.06	0.0000	4.22	0.0000	Nonlinear
MKTWGHT	3.88	0.0001	3.87	0.0001	4.31	0.0000	4.45	0.0000	Nonlinear
MKT2WGHT	4.55	0.0000	4.01	0.0000	3.77	0.0001	3.64	0.0002	Nonlinear

3.4.4 Empirical results and discussion

3.4.4.1 Herding behaviour results based on the static approach

This study begins by analysing herding behaviour in the context of the static model. The results are presented in Table 3.9.

Table 3.9: Regression results for the static model using the OLS

$Dispersion_t = \alpha + \varphi_1\left|R_{m,t}\right| + \varphi_2 R_{m,t}^2 + Dispersion_{t-1} + \varepsilon_t$				
	Weekly		Monthly	
	$CSAD_t$	$CSADWGHT_t$	$CSAD_t$	$CSADWGHT_t$
α	0.6026*** (14.614)	0.0162*** (18.079)	1.3317*** (9.217)	0.0564*** (9.867)
φ_1	0.5004*** (6.258)	1.1589*** (29.804)	0.4199*** (3.670)	0.8052*** (6.850)
φ_2	0.2144*** (4.430)	0.8353*** (2.872)	0.0591*** (3.474)	1.7646*** (3.409)
φ_3	0.0967*** (3.021)	0.0564*** (3.890)	0.2129*** (3.559)	0.0136*** (0.455)
LL	-442.54	3033.3	-301.36	490.41
AIC	893.1	-6059	610.7	-972.8
BIC	913.0	-6039	624.7	-958.8
Adj. R^2	0.653	0.882	0.487	0.782

Note: *, **, *** Indicate significant at the 10%, 5% and 1% level of significance respectively. The numbers in parenthesis are the values of the statistical t-ratios based on the Newey-West consistent estimators. LL denotes log-likelihood of the OLS method, AIC represents the Akaike Information Criterion $=-2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})$. BIC denotes Bayes-Schwartz Information Criterion $=-2\ln L(\widehat{\Theta}) + dim(\widehat{\Theta})\ln T$.

The static model results reveal absence of herding evidence as shown by positive coefficients φ_2 for both weekly and monthly data. In other words the return dispersion as measured as proxied by the equally weighted cross sectional absolute deviation (CSAD) and value weighted (CSADWGHT) increase with the absolute market returns. The findings in this study are in contrast to Guney *et al*. (2017) for the NSX. Guney *et al.* (2017) finds evidence of herding behaviour for the all equity stocks employing the OLS and daily data in contrast to this study that employs weekly and monthly data to mitigate thin trading problem. Noteworthy from Table 3.9 is the detection of significant anti-herding or negative herd behaviour as evidenced by positive and statistically significant coefficient φ_2.

3.4.4.2 Herding behaviour results under different regimes

Estimates of the two-regime herding model are presented in Table 3.10 below. Besides the likelihood values, the selection criterions such as Akaike Information Criterion (AIC) and Bayes-Schwartz Information Criterion (BIC) are also calculated in order to provide a trade-off between parsimony and goodness of fit of the model. The Markov regime switching models in Table 3.10 have substantially larger log-likelihood and smaller criteria values than their counterpart static models in Table 3.9. This shows that the Markov regime switching models are statistically superior to the static models which supports the preference of the former to the later. Results in Table 3.10 show that the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for the whole market.

Table 3.10: Regime switching model results

	Weekly		Monthly	
Parameter	$CSAD_t$	$CSADWGHT_t$	$CSAD_t$	$CSADWGHT_t$
α_1	0.5035***	0.0157***	1.5176***	0.1245***
α_2	0.9014***	0.0288***	0.1504***	0.0442***
φ_{11}	0.5831***	1.0802***	0.2124***	0.7591***
φ_{12}	1.0293***	1.4968***	4.2736***	0.8530***
φ_{21}	0.0749***	1.5645***	0.0882***	1.9139
φ_{22}	0.1395***	-1.8482***	-0.6643***	1.3817***
φ_{31}	0.1187***	0.0311***	0.1533***	-0.1668*
φ_{32}	-0.0159***	0.1268***	0.2410	0.0440*
σ_1	0.0420***	0.0001***	0.3101***	0.001***
σ_2	0.2398***	0.0005***	0.6329***	0.003***
p_{11}	0.8480***	0.8806***	0.9506***	0.4296***
p_{22}	0.6266***	0.8264***	0.7652***	0.1117***
τ_1	6.57	8.37	20.26	1.75
τ_2	1.59	1.21	1.30	8.95
n	1077	1077	246	246
$\log L$	-213.533	3263.289	-243.938	544.248
AIC	451.066	-6502.578	511.876	-1064.496
BIC	510.849	-6442.795	553.940	-1022.432
HQIC	473.706	-6479.938	528.813	-1047.559

Notes: This table presents results of the following two regime Markov switching model:

$Dispersion_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}Dispersion_{t-1} + \sigma_{s_t}\varepsilon_t$, where$p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$

τ_k denotes the duration of regime k; HQIC denotes Hannan-Quinn Information Criterion $= -2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})\ln T$.

*, **, *** Indicate statistically significant at 10%, 5% and 1% level respectively

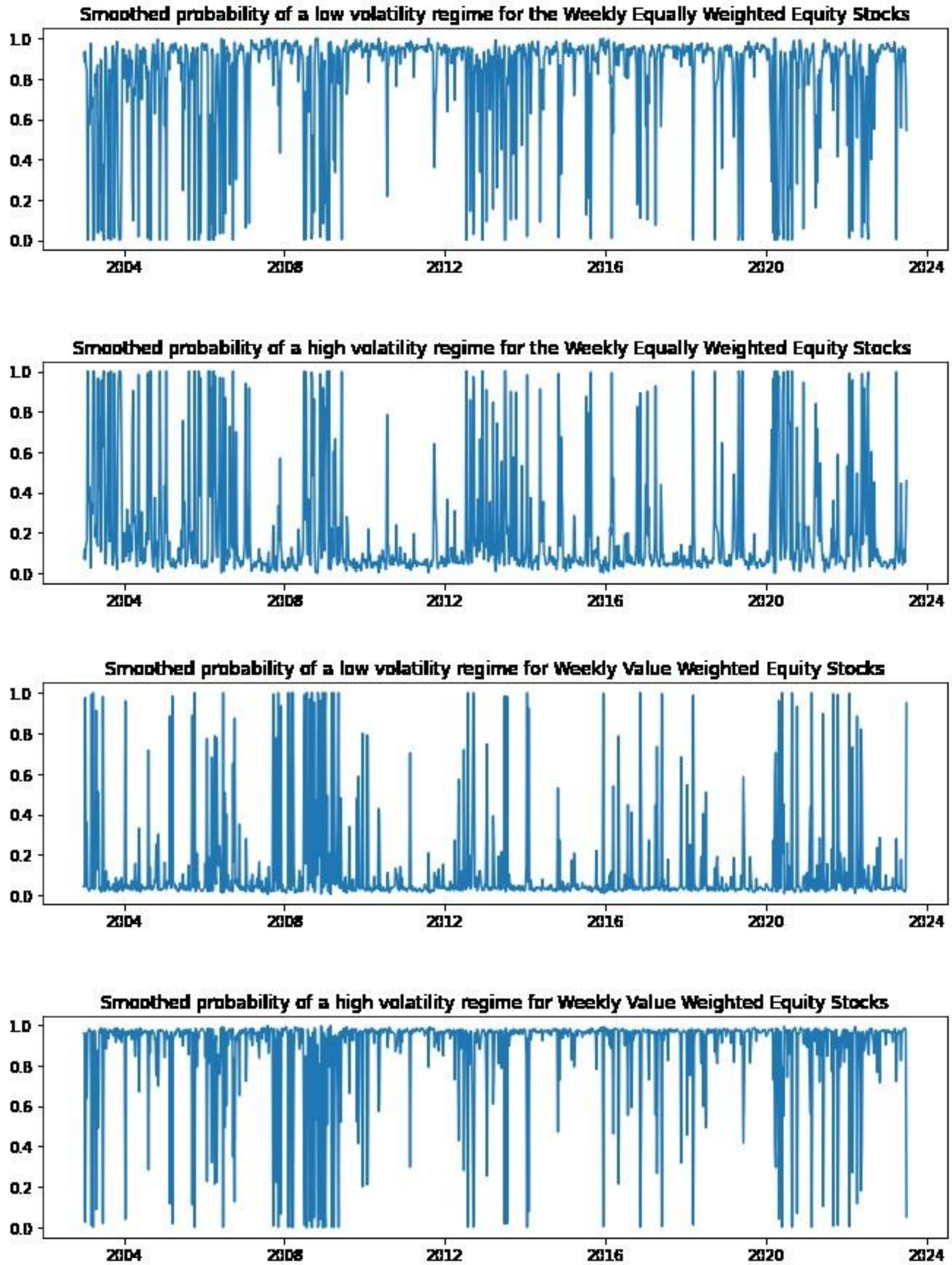
Thus $\hat{\sigma}_2$ corresponds to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime (tranquil regimes). The state transition probabilities are statistically significant which indicates stability of the hidden market regimes inferred from the models and have tendency of remaining in the current regimes. The transition probability of switching from high volatility regime to a low one is estimated as $1 - \hat{p}_{22}$, whereas the transition probability from low volatility state to a high one is estimated as $1 - \hat{p}_{11}$. In this regard, the transition probabilities of moving from a high volatility to a low volatility are 0.7337 and 0.1736 using the weekly equally and value weighted cross-sectional absolute deviation respectively and also 0.2348 and 0.8883 using the monthly equally and value weighted cross-sectional absolute deviation respectively. Conversely, the transition probabilities of moving from a low volatility state to a high one are 0.152 and 0.1194 using the weekly equally and value weighted cross-sectional absolute deviation respectively and also 0.0494 and 0.5704 using the monthly equally and value weighted cross-sectional absolute deviation respectively.

Besides volatility clustering, the transition probabilities above also reflects that the high volatility state is less persistent and stable than the low volatility state. Besides, the non-diagonal elements of the transition probability matrices are much less than their diagonal counterparts suggesting the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 3.10, the whole market exhibits herding behaviour under the high volatility regime using both weekly and monthly data. This is also consistent with findings by Babalos *et al.* (2015) and Mand and Sifat, (2021). A possible explanation of this findings is that investors tend to discard their own convictions and mimic other's actions during high volatility than during the tranquil one. Remarkably, there is no evidence of herding behaviour for the monthly value weighted approach. This empirical findings supports the notion by Lakonishok *et al.* (1992) that herding behaviour effects is overstated in smaller firms due to poor flow of information

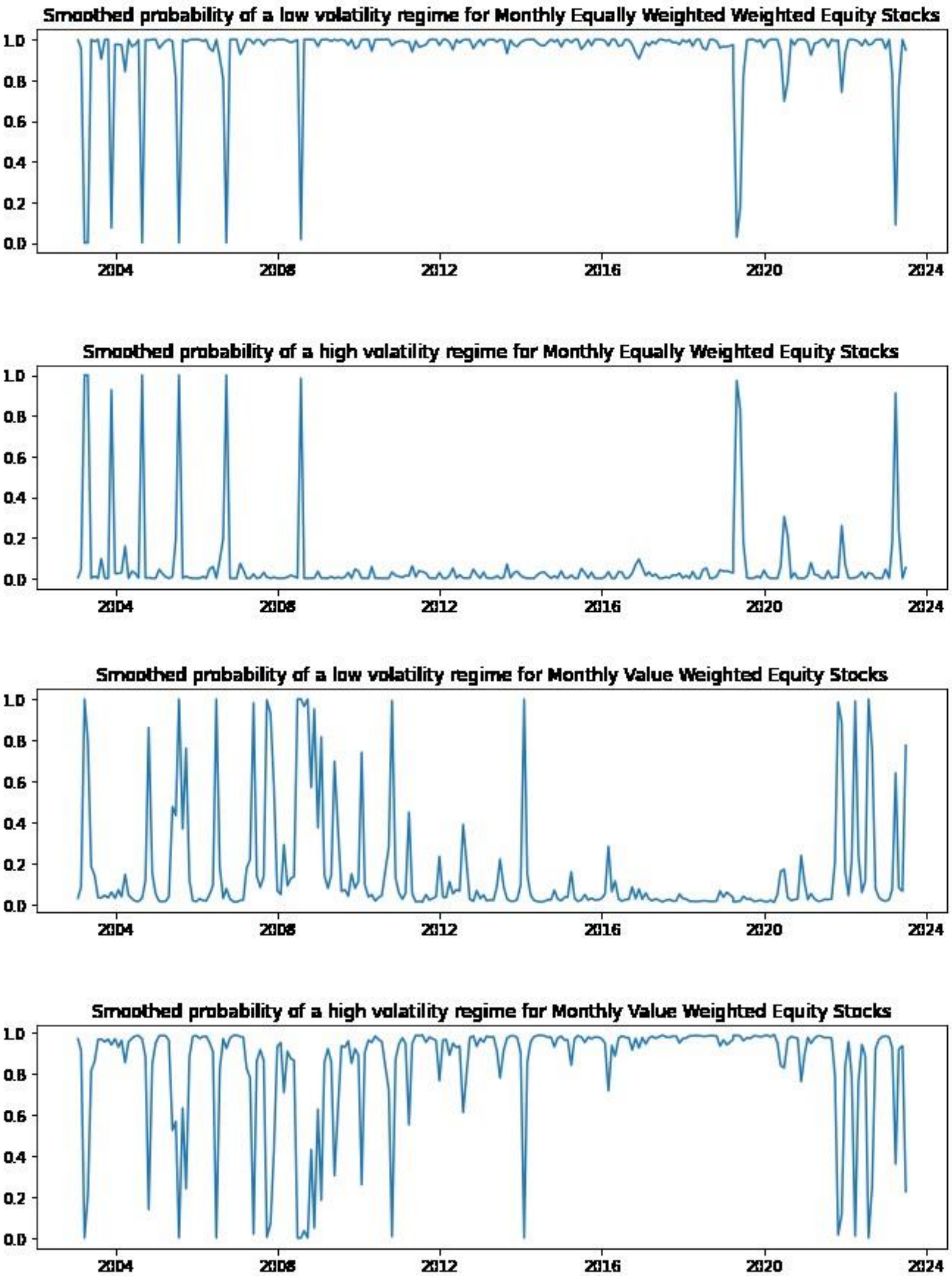
Table 3.10 also provides the expected durations of the market regimes. The low volatility regime tend to the most persistent regime as indicated by the longest average regime durations save for the monthly value weighted cross-sectional absolute deviation. Figures 3.9 and 3.10 show the smoothed probability plots for visual inspection of the dynamic nature of the state transitions and herding behaviour. The smoothed probability plots suggest existence of the herding behaviour during the 2008-09 Global Financial Crisis period and the recent COVID-19 pandemic. The smoothed probability plots in Figures 3.9 and 3.10 tend to suggest a low-high (LH) volatility transition order in which the high volatility regimes follows the low volatility regimes. In this regard, the low-volatility regimes plays as a major role in giving warning to the financial market regulators before the high volatility regime. Furthermore, the smoothed probability regimes between the low and high volatility regimes suggest a bi-directional transitions. In this regard, financial market regulators can play a pivotal role during uncertainties periods in avoiding possible transitions to high volatility regimes.

Figure 3.9: Smoothed probabilities for All Equity Stocks using weekly data



Source: Python results (2024)

Figure 3.10: Smoothed probabilities for All Equity Stocks using monthly data



Source: Python results (2024)

3.5 Conclusions and policy implications

This research examines the existence of herding behaviour dynamics in the NSX for the period 01 January 2003 to 30^{th} June 2023. Cross sectional absolute standard deviation (CSAD) was used as an alternative measure of herding behaviour to the traditional cross-sectional standard deviation proposed by Christie and Huang (1995). As pointed by Lakonishok *et al.* (1992) herding behaviour tends to be pronounced in small firms than large firms due to poor flow of information in the former. To eliminate the herding behaviour effect bias of small firms in a data series, the weekly and monthly stock returns in this research were weighted by the week-end and month-end total market capitalization of all the firms as done by Guney *et al.* (2017).

The herding behaviour models in this research were first estimated using the static model as the benchmark and then using the Markov-Regime Switching Model (MRSM) which overcomes most financial time series problems such as fat tails, volatility clustering and non-normality characteristics in a data series which is not possible under the OLS method. In all the estimation models, the OLS results points to a linear relationship between stock market dispersions as measured by equally and value weighted CSAD and stock market returns indicative of the absence of herding behaviour in the NSX for the period under review. However, herding behaviour is detected in high volatile regimes after utilising the MRSM. This also corroborates with the findings by previous researchers such as Economou *et al.* (2016) and Chaffai and Medhioub (2018) who highlighted that herding behaviour tends to occur in high volatile regimes, due to hefty price movements and unpredictable market conditions. Thus we can conclude existence of herding behaviour in the NSX in the volatile regime conditions which is consistent with some previous research highlighted above. This means investors in the NSX tend to follow each other when market profits are high and works in harmony.

The findings of this current study may be of significance to the current and potential investors, management of firms listed on the NSX and Namibian policy makers. Firstly, knowledge of herding behaviour may help current and potential investors in the NSX in the asset allocation process and diversification of risk since herding behaviour often leads to market inefficiency. Secondly, management of firms listed on the NSX should improve transparency in terms of disclosure of published financial statements inorder to induce investors' confidence. Thirdly, Namibian policy makers should improve transparency in the NSX through sound legislative framework and afford equal opportunity to all investors in terms of vital communication for investment decision making.

Some of the limitations of this research include the utilisation of weekly and monthly market returns as an alternative to daily market returns. However, medium and long time market returns tends to be affected by price age which is another component of thin trading as pointed by Mlambo *et al.* (2003). Price age refers to the time between the last trade and the trade at the end of the period. This means if there is no trade at the end of the period, the last trade price is taken as the price at the end of the period. Therefore, future research in this area should also try to address the issue of price age in the long time horizon data series to address the issue of thin trading. However, adjusting for price age tend to be a complex situation particularly in emerging markets like the NSX due to unavailability of closing prices for periods less than a day like hourly closing prices. More so, the chance of stock having traded during that short time frame is also slim especially in the emerging markets. Despite the challenge, it could be interesting for future research to factor in price age in the long time horizons market returns when estimating herding behaviour.

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Chapter 4: A Markov switching model to sectoral herding behaviour: Novel evidence from the Namibian Securities Exchange (NSX)

Abstract

This study examines the presence of sectoral herding behaviour in the NSX using the Markov Regime Switching Model (MRSM). Employing the weekly and the monthly data from 1st January 2003 to 30th June 2023, the results of the static model reveals non-existence of herding behaviour for all the sectors, save for the Industrials sector utilizing the value weighted weekly data . However, the dynamic approach utilising the two-regime Markov switching model reveals substantive evidence of herding behaviour for the Industrial and Resource sectors. Most interestingly herding behaviour is observed to exist under both the high and low volatility regimes. In this regard, present and future investors are recommended to come up with a larger investment portfolio in order to reach the same diversification goal in more volatile states.

Key words

Herding behaviour, Market stress, Markov Regime-Switching model, and Sectoral herding

4.1 Introduction

The topic on herding behaviour continue to gain attention particularly due to the important role it plays in the financial markets development. Herding behaviour refers to a situation when investors or market participants disregard their own beliefs or convictions and mimic the actions of others. The health status of an economy can be gauged through the stock markets (Mand & Sifat, 2021). Mand and Sifat (2021) further noted that stable equity markets are a reflection of market participants' sanguine bet on the state of the economy. Herd behaviour tend to distorts asset prices and their fundamentals values which can lead to bubbles and financial crashes in worst scenarios (Cakan & Balagyozyan, 2014). Thus herding behaviour plays a major role in asset pricing models and the efficient market hypothesis (EMH) as risk return distributions are distorted in the asset markets. The equity market is assumed to be efficient if all the relevant information is reflected in the stock prices.

This current study fills the gap on the existing literature on herd behaviour by analysing sectoral herd behaviour in emerging markets focusing on the NSX. There are a number of reasons which motivates undertaking this study. Firstly, the NSX has grown by leaps and bounce since its establishment in 1992. It attracts a lot of foreign and institutional investors, due to its direct linkage to the Johannesburg Stock Exchange (JSE) as most firms are dually listed. Foreign and institutional investors tend to be sophisticated than individual investors due to information asymmetry and tend to follow the actions of others (Cakan & Balagyozyan, 2014). Secondly, there is very little existing literature analysing herd behaviour in the NSX thereby leaving a lot of areas in need of attention. This is the first research to analyse sectoral herding in the NSX. To the researcher's knowledge, the only paper so far on the herding behaviour in the NSX focuses on the whole market leaving the cross-sectoral idiosyncrasies untapped. Thirdly, the only paper highlighted above uses the static approach. The current study goes one step further and proposes the Markov-switching regime model which is able to capture time-varying phenomenon of herd behaviour, not only for the whole market but also from the sectoral perspective. The rest of this study is structured as follows: section 4.2 highlights herd behaviour literature, section 4.3 presents the methodology, section 4.4 presents and discusses the results and section 4.5 provides some concluding remarks.

4.2 Literature review

Literature on herding behaviour emanates from two streams of theories. On one hand is the particular stock herding while on the other hand is the market-wide herding (Mand & Sifat, 2021).In the first scenario, individuals or a group of investors concentrate only on a subcategory of securities, while abandoning other stocks with similar features. Some notable studies for the group-wide herding are Lakonishok *et al*. (1992) and Schmitt and Westerhoff (2017). These studies utilise detailed transaction data to analyse the herd behaviour of different market participants such as speculators and fund managers. In the market-wide herding scenario, investors monitors market movements and make a move based on these market trends. Notable studies on the market-wide herding includes: Christie and Huang (1995); Chang *et al*. (2000) ; and Chiang and Zheng (2010). Christie and Huang (1995) developed a model to capture herding behaviour in the US stock market utilising the cross-sectional standard deviation of market returns (CSSD). Chang *et al.*

(2000) modified the model by Christie and Huang (1995) and employed the cross-sectional absolute deviation of market returns (CSAD) instead of the CSSD to capture herding behaviour of the Hong Kong, Japanese, South Korea and Taiwanese and USA stock markets. Based on a study of 18 countries from 1988 to 2009, Chiang and Zheng (2010) find that herding tend to be less likely to happen for the investors with access to high quality micro-economic information (Mand & Sifat, 2021).

On the empirical side a number of studies have been carried so far in developed and developing markets to analyse sectoral herding behaviour. Some of the notable studies are summarized in Table 4.1 below. Notable studies from Europe includes: Litimi (2017), Cakan and Balagyozyan (2014) and Cakan and Balagyozyan (2016). Employing the CSAD measure, OLS and GARCH models for the French stock market, Litimi (2017) found absence of herding behaviour for the whole market but present in the consumer good, consumer services, financials, oil and gas and others sectors. The findings were in contrast to Cakan and Balagyozyan (2016) who found evidence of herding for the whole market employing the OLS for the Turkish Stock market. However, Cakan and Balagyozyan (2016) found evidence of herding behaviour for the financials, industrials, services, and technology sectors.

Notable studies from Asian continent includes: Ahmed *et al*. (2019); Elshqirat (2019); Fu and Wu (2020); Lam and Qiao (2015); and Mand and Sifat (2021). Ahmed *et al.* (2019) find evidence of herding behaviour for the whole market employing the Hwang and Salmon herding measure. This result was also consistent to finding by Lam and Qiao (2015) for the Hong Kong employing the OLS and GARCH models but in contrast to

Elshqirat (2019) for the Jordan stock market. Fu and Wu (2020) and Mand and Sifat (2021) find evidence of herding behaviour for the whole market employing the Markov Switching models for the Chinese and Malaysian stock markets. On sectorial level, Ahmed *et al.* (2019); Elshqirat (2019); Fu and Wu (2020); Lam and Qiao (2015); and Mand and Sifat (2021) also find evidence of herding behaviour on the sectoral level.

There is very little existing sectoral herding behaviour literature on the African context. One of the notable studies is by Ababio and Mwamba (2017). Employing the Quantile Regression (QR) approach for the Johannesburg Stock Exchange, Ababio and Mwamba (2017) found evidence of herding behaviour in the banking (when market is falling) and real estate sectors (when market is rising). For the entire financial industry, herding is found during extreme upmarket period. Despite the effort so far, there is a still a big huge gap existing in terms of sectoral herding behaviour literature especially in the Namibian context which is one major contribution of this current study.

Table 4.1: Summary of the empirical studies on sectoral herding behaviour

Country	Authors	Period	Methodology	Conclusion
Chinese A-Share market	Fu and Wu (2020)	Daily and monthly stock prices from 1999-2016	Two-state Markov Switching model employing the CH herding measure	The results revealed novel evidence of herding during the volatile regime for all the 29 sectors
France	Litimi (2017)	Daily data for the period 2000 to 2016	OLS and GARCH employing the modified CCK herding measure	The results indicated presence of herding behaviour during crises period in the consumer good, consumer services, financials, oil and gas and others sectors.
Hong Kong	Lam and Qiao (2015)	Daily data from 1986-2007	OLS and GARCH employing the CH and CCK herding measures	The OLS and GARCH results revealed evidence of herding for the Finance, Utilities, Consolidated Enterprises and Industrial sectors.
Jordan	Elshqirat (2019)	Daily data from 2000-2008	OLS employing the CCK herding measure	The OLS results revealed absence of herding for the whole market but existence of herding for the services and industrial sector
Malaysia	Mand and Sifat (2021)	Daily data for period 1995-2016	Two-state Markov Switching employing CH and CCK herding measure	The results revealed evidence of herding behaviour for the financial and manufacturing sector.
Pakistan	Ahmed *et al.* (2019)	Monthly data from 2013-2018	Employing HS herding measure	The results revealed evidence of herding for the cement and textile sectors
South Africa	Ababio and Mwamba (2017)	Daily data for the period 2010-2015	QR employing the CCK herding measure	The results revealed evidence of herding behaviour in the banking (when market is falling) and real estate sectors

				(when market is rising). For the entire financial industry, herding is found during extreme upmarket period.
Turkey	Cakan and Balagyozyan, (2014)	Daily data from 2007-2012	OLS utilising the CCK herding measure	The results revealed evidence of herding for the banking sector when the market is rising
Turkey	Cakan and Balagyozyan (2016)	Daily data from 2002-2014	OLS employing the CCK herding measure	The results revealed evidence of herding for all the four sectors (financials, industrials, services, and technology). It is pronounced in the high volatile markets for the financials, services and technology. During low volatile markets, herding is found in the services sector.
US-listed Real Estate Investments Trusts (REITS)	Babalos *et al*. (2015)	Daily returns for period 2004-2013	Three-state Markov Switching model employing the CCK herding measure	The results revealed evidence of herding behaviour for the REITS sectors (Industrial, Retail and Residential) during the crash regime

Note: OLS, GARCH, CH, CCK, HS refers to Ordinary Least Squares, Generalised autoregressive conditional heteroscedasticity, Christie and Huang, Chang, Cheng and Khorana, Hwang and Salmon respectively.

4.3 Methodology and data

4.3.1 Sectoral static approach to herd behaviour

As illustrated in the previous chapter, the sectoral static approach is specified as follows:

$$Dispersion_t = \alpha + \varphi_1 |R_{m,t}| + \varphi_2 R_{m,t}^2 + Dispersion_{t-1} + \varepsilon_t \quad (4.1)$$

Where: $Dispersion_t$ represents both the equally and value weighted CSAD for each sector.

4.3.2 Sectoral regime switching model for herd behaviour

As explained in the previous chapter, the two (2) state sectoral Markov Switching regime model in this study is specified as explained in the previous chapter:

$$Dispersion_t = \alpha_{0,s_t} + \delta_{1,s_t} |R_{m,t}| + \delta_{2,s_t} R_{m,t}^2 + \delta_{3,s_t} Dispersion_{t-1} + \sigma_{s_t}\varepsilon_t \quad (4.2)$$

Where: $Dispersion_t$ denotes both the equally and value weighted sectoral CSAD.

4.3.3 Data description

The sectoral data in this study was collected from the NSX. The company listed on NSX were divided into the following four main sectors: Financials, Industrials, Resources, and Services. Weekly and monthly data were utilised in this study to mitigate the issue of thin trading as explained in the previous chapter.

4.4 Results and analyses

4.4.1 Descriptive statistics

Table 4.2 through 4.5 below provides the descriptive statistics for the data used in this study. It is imperative to note that the number of firms in each respective sector does not remain constant for the period under review. As a result the number of stocks used in calculating the return dispersion changes over time. From Table 4.2 the average equally weighted weekly returns range between a low figure of -0.018 for the Resources sector and a high of 0.065 for the Industrial sector, whilst that of the value weighted in Table 4.3 ranges from a low figure of 0.002 for both the Financials and Industrials to a high of 0.022 for the Services sector. For the period under review, all the sectors have had positive monthly return means save for the Resources (equally weighted) which may point to the better performance of the NSX in the short term in almost all the sectors.

The volatility of equally weighted weekly returns as measured by the standard deviation in Table 4.2 ranges from a low of 0.667 for the Financials sector to a high of 1.515 for the Resources sector whilst for the value weighted weekly returns in Table 4.3 range from a low of 0.072 (Financials Sector) to a high of 0.579 (Resources Sector). This observation may point to the fact that the stocks in the financial sector tend to have the behaviour similar to the group and thus the standard deviation of this sector tend to be the smallest compared to other sectors. This observation might be due to the fact that this sector tend to be more regulated and supervised compared to other sectors. From Table 4.2 the most extreme changes in the equally weighted weekly returns can be observed in the Services sector and the Industrials sector with a minimum of -13.41 and a maximum of 20.16

respectively, whilst that of the value weighted weekly returns in Table 4.3 can be observed in the Industrial sector and Services sector with a minimum of -5.005 and a maximum of 3.704

From Table 4.4 the average equally weighted monthly returns range between a low figure of -0.070 for the Resources sector and a high of 0.230 for the Services sector whilst that of the value weighted in Table 4.5 ranges from a low figure of -0.001 (Industrials sector) to a high of 0.083 for the Resources sector. For the period under review, all the sectors have positive monthly returns save for the Resources (equally weighted) and Industrials (value weighted) which may point to the better performance of the NSX in the long term in almost all the sectors.

The volatility of equally weighted monthly returns as measured by the standard deviation in Table 4.4 ranges from a low of 1.64 for the financials sector to a high of 3.47 for the Resources sector whilst for the value weighted monthly returns in Table 4.5 range from a low of 0.144 (Financials Sector) to a high of 1.162 (Resources Sector). From Table 4.4 the most extreme changes in the equally weighted monthly returns can be observed in the Services sector and the Industrials sector with a minimum of -14.25 and a maximum of 17.57 respectively whilst that of the value weighted monthly returns in Table 4.5 can be observed in the Services sector and Resources sector with a minimum of -6.141 and a maximum of 5.118.

The data series in this study especially measures of dispersion are characterised by higher level of leptokurtosis as seen by the kurtosis and skewness values greater than 3 as presented in Table 4.2 through Table 4.5. Furthermore, the Jarque-Bera results indicated that we reject the null hypothesis of normality and conclude that the data is non-normal.

The hexagonal binning properties of the return dispersions and the market returns for both the whole market and relevant sectors are illustrated in Figure 4.1 through 4.4. It can observed from Figure 4.1 through 4.2 that the non-linearity between return dispersion and market returns is obvious. Thus, the prediction of nonlinear reversal relationship between return dispersions and market returns can be confirmed which is line with Christie and Huang (1995) and Chang *et al.* (2000). Results of the Augmented Dickey Fuller (ADF) test indicates that we reject the null hypothesis in all the variables and conclude the time series is stationary. Thus, estimations in this study is done without the fear of getting spurious results.

Table 4.2: Descriptive statistics of the equally weighted weekly data

Panel A: CSAD										
Sector	#Firms	n	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Jarque-Bera	ADF
Financials		1077	0.816	0.586	0.103	8.726	44.855	4.875	93685.255***	-9.210**
Industrial		1077	1.100	1.567	0.003	33.798	180.636	10.006	1468542.569***	-3.607**
Resources		1077	1.340	1.080	0.027	15.817	34.480	3.784	55405.059***	-8.629**
Services		1077	1.066	1.363	0.021	22.169	86.204	7.629	340771.174***	-25.757**
Panel B: MKT										
Financials	17	1077	0.035	0.667	-5.689	4.276	10.763	-0.760	5249.344***	-12.685**
Industrial	5	1077	0.065	1.306	-8.325	20.164	58.257	3.574	153151.248***	-27.043**
Resources	3	1077	-0.018	1.515	-9.670	11.080	7.098	0.337	2257.372***	-32.771**
Services	9	1077	0.042	1.266	-13.409	8.249	17.931	-0.873	14423.465***	-25.591**
Panel C: MKT2										
Financials		1077	0.447	1.580	0.0000000014	32.372	210.059	12.682	1990475.923***	-12.935**
Industrial		1077	1.708	13.286	0.0000000085	406.592	806.456	26.921	29044742.560***	-17.435**
Resources		1077	2.293	6.900	0.000000334	122.766	156.914	10.870	1115775.594***	-17.065**
Services		1077	1.604	7.123	0.000000168	179.818	380.539	16.921	6489308.258***	-28.413**

Notes: The Augmented Dickey Fuller (ADF) test is used to test for stationarity in the data series

, * Indicate statistically significant at 5% and 1% level respectively

Table 4.3: Descriptive statistics of the value weighted weekly data

Panel A: CSADWGHT										
Sector	#Firms	n	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Jarque-Bera	ADF
Financials		1077	0.081	0.061	0.007	0.582	11.851	2.688	7532.813***	-4.693**
Industrial		1077	0.333	0.359	0.001	4.671	28.805	4.004	39746.210***	-3.822**
Resources		1077	0.576	0.527	0.0017	4.059	5.447	1.912	1971.026***	-4.704**
Services		1077	0.279	0.296	0.0057	6.882	229.696	11.171	2367952.535***	-8.178**
Panel B: MKTWGHT										
Financials	17	1077	0.002	0.072	-0.479	0.410	5.083	-0.091	1147.984***	-10.714**
Industrial	5	1077	0.002	0.386	-5.005	2.308	30.835	-1.994	42971.857***	-12.923**
Resources	3	1077	0.008	0.579	-2.479	2.823	2.461	0.255	279.772***	-25.701**
Services	9	1077	0.022	0.351	-1.239	3.704	16.233	1.565	12147.413***	-6.955**
Panel C: MKT2WGHT										
Financials		1077	0.005	0.013	0.0000000016	0.230	97.780	8.285	437322.610***	-5.464**
Industrial		1077	0.149	0.854	0.0000000041	25.054	676.051	23.823	20421452.078***	-17.063**
Resources		1077	0.335	0.708	0.000000235	7.971	38.615	5.250	71211.783***	-4.755**
Services		1077	0.123	0.531	0.000000223	13.722	441.749	19.009	8740490.784***	-8.518**

Notes: The Augmented Dickey Fuller (ADF) test is used to test for stationarity in the data series

, * Indicate statistically significant at 5% and 1% level respectively

Table 4.4: Descriptive statistics of the equally weighted monthly data

Panel A: CSAD										
Sector	#Firms	n	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Jarque-Bera	ADF
Financials		246	2.001	1.287	0.552	12.034	21.762	3.803	5235.428***	-5.709**
Industrial		246	2.486	2.461	0.174	28.856	53.655	5.631	29585.819***	-3.567**
Resources		246	3.021	2.186	0.185	16.524	9.578	2.443	1139.876***	-5.865**
Services		246	2.523	2.677	0.209	27.027	37.721	5.410	15168.995***	-3.294**
Panel B: MKT										
Financials	17	246	0.147	1.637	-7.711	4.614	5.155	-1.299	327.434***	-14.391**
Industrial	5	246	0.179	2.492	-9.361	17.570	10.326	0.994	1084.395***	-15.209**
Resources	3	246	-0.070	3.470	-11.861	14.971	1.874	1.874	34.110***	-16.694**
Services	9	246	0.230	2.634	-14.252	13.957	6.546	-0.390	424.752***	-16.330**
Panel C: MKT2										
Financials		246	2.690	6.866	0.000011	59.462	41.255	6.008	18189.788***	-14.461**
Industrial		246	6.218	21.827	0.0000000009	308.738	152.466	11.342	233872.747***	-13.570**
Resources		246	11.999	23.447	0.000225	224.133	32.016	4.745	10982.770***	-12.141**
Services		246	6.965	19.937	0.00000034	203.136	70.021	7.723	50627.409***	-3.280**

Notes: The Augmented Dickey Fuller (ADF) test is used to test for stationarity in the data series

, * Indicate statistically significant at 5% and 1% level respectively

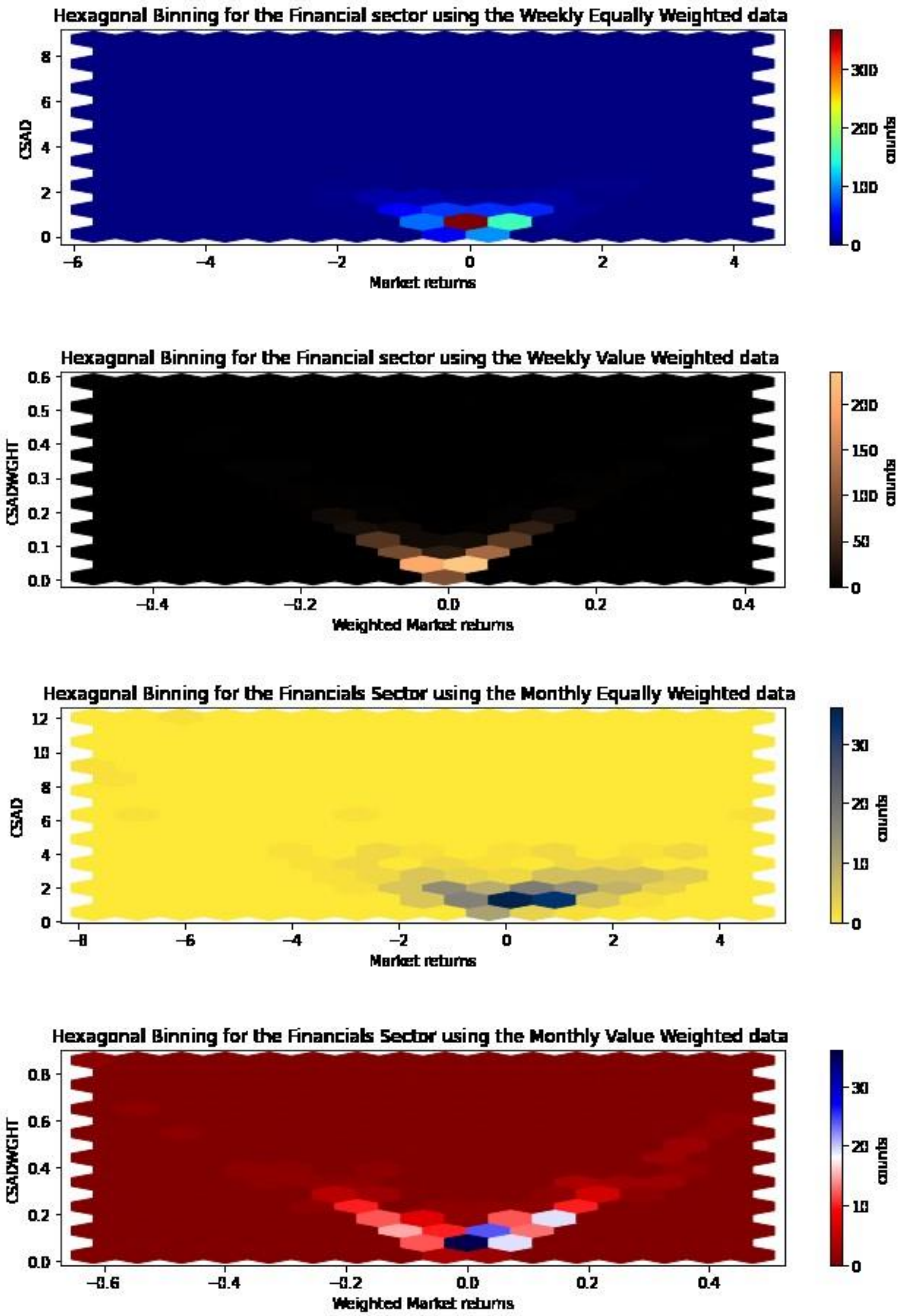
Table 4.5: Descriptive statistics of the value weighted monthly data

Panel A: CSADWGHT										
Sector	#Firms	n	Mean	Std. Dev.	Min.	Max.	Kurtosis	Skewness	Jarque-Bera	ADF
Financials		246	0.170	0.110	0.024	0.855	8.026	2.245	834.191***	-3.453**
Industrial		246	0.775	0.782	0.049	8.160	34.214	4.524	12331.240***	-2.254**
Resources		246	1.227	0.983	0.018	7.448	7.295	1.977	678.482***	-5.537**
Services		246	0.697	0.873	0.058	11.100	91.495	8.458	85226.902***	-15.782**
Panel B: MKTWGHT										
Financials	17	246	0.015	0.144	-0.616	0.471	2.211	-0.383	52.984***	-15.941**
Industrial	5	246	-0.001	0.901	-6.096	2.806	13.589	-2.303	2025.440***	-13.660**
Resources	3	246	0.083	1.162	-3.506	5.118	1.567	0.292	26.881***	-16.937**
Services	9	246	0.079	0.812	-6.141	3.557	14.402	-1.517	2127.401***	-16.686**
Panel C: MKT2WGHT										
Financials		246	0.021	0.042	0.000000453	0.380	29.331	4.733	9358.820***	-14.267**
Industrial		246	0.810	3.175	0.000002	37.165	95.869	9.279	93878.970***	-15.956**
Resources		246	1.351	2.562	0.000135	26.199	39.879	5.283	16760.319***	-8.290**
Services		246	0.663	2.596	0.000000930	37.715	172.366	12.403	298492.674***	-15.821**

Notes: The Augmented Dickey Fuller (ADF) test is used to test for stationarity in the data series

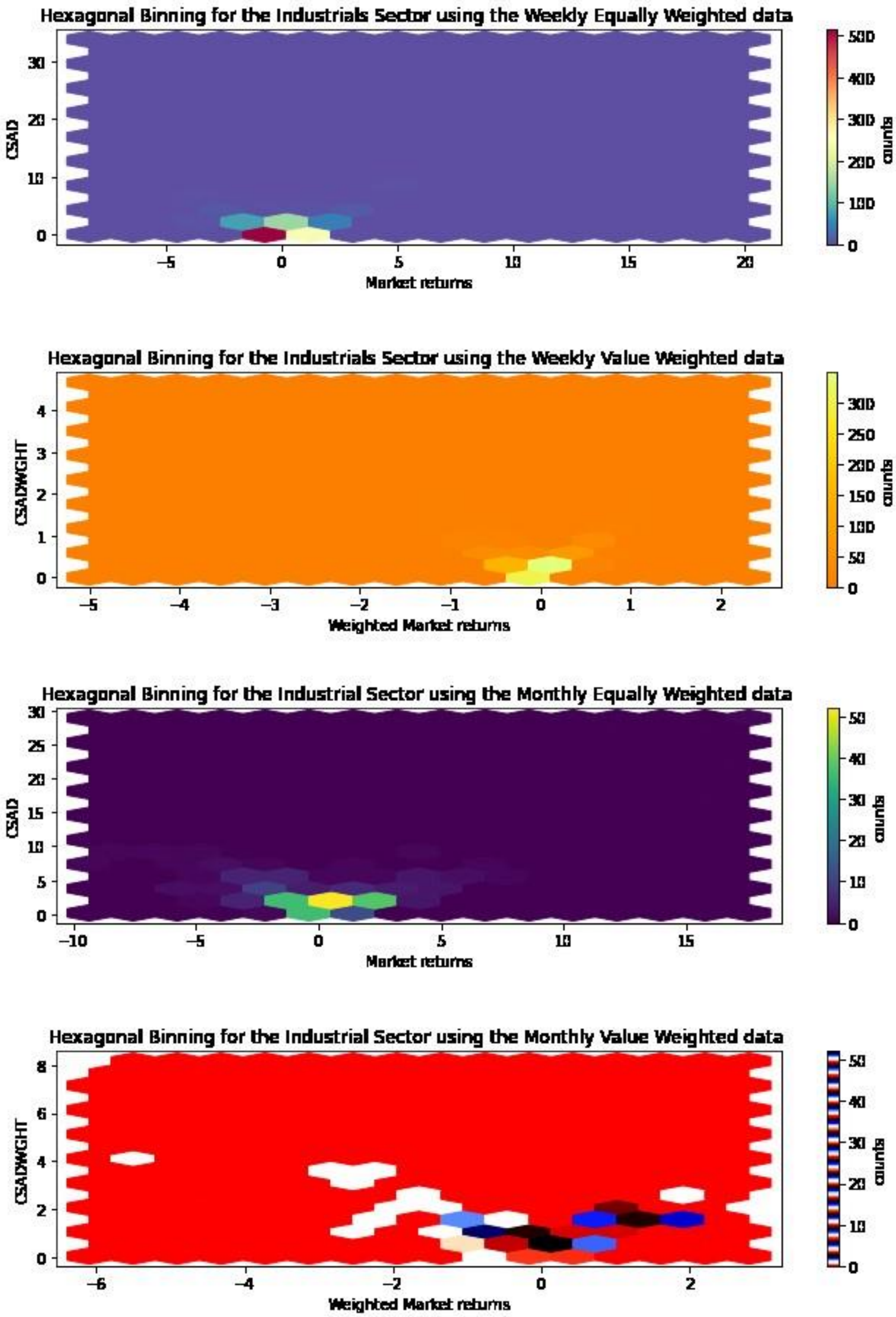
, * Indicate statistically significant at 5% and 1% level respectively

Figure 4.1: Hexagonal binning showing distributive properties of cross-sectional absolute deviations and Market returns for the Financials Sector



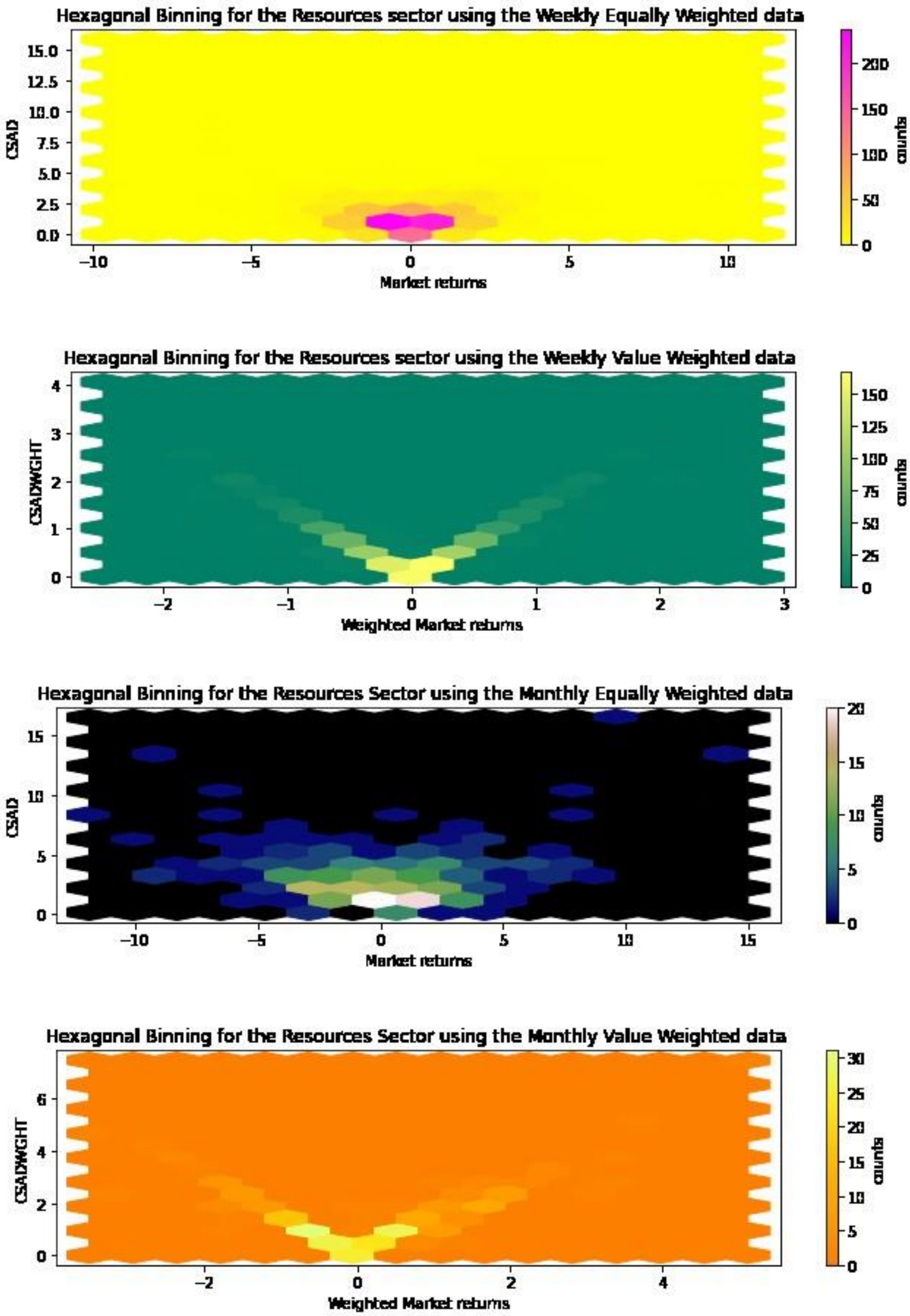
Source: Python results (2024)

Figure 4.2: Hexagonal binning showing distributive properties of cross-sectional absolute deviations and Market returns for the Industrials Sector



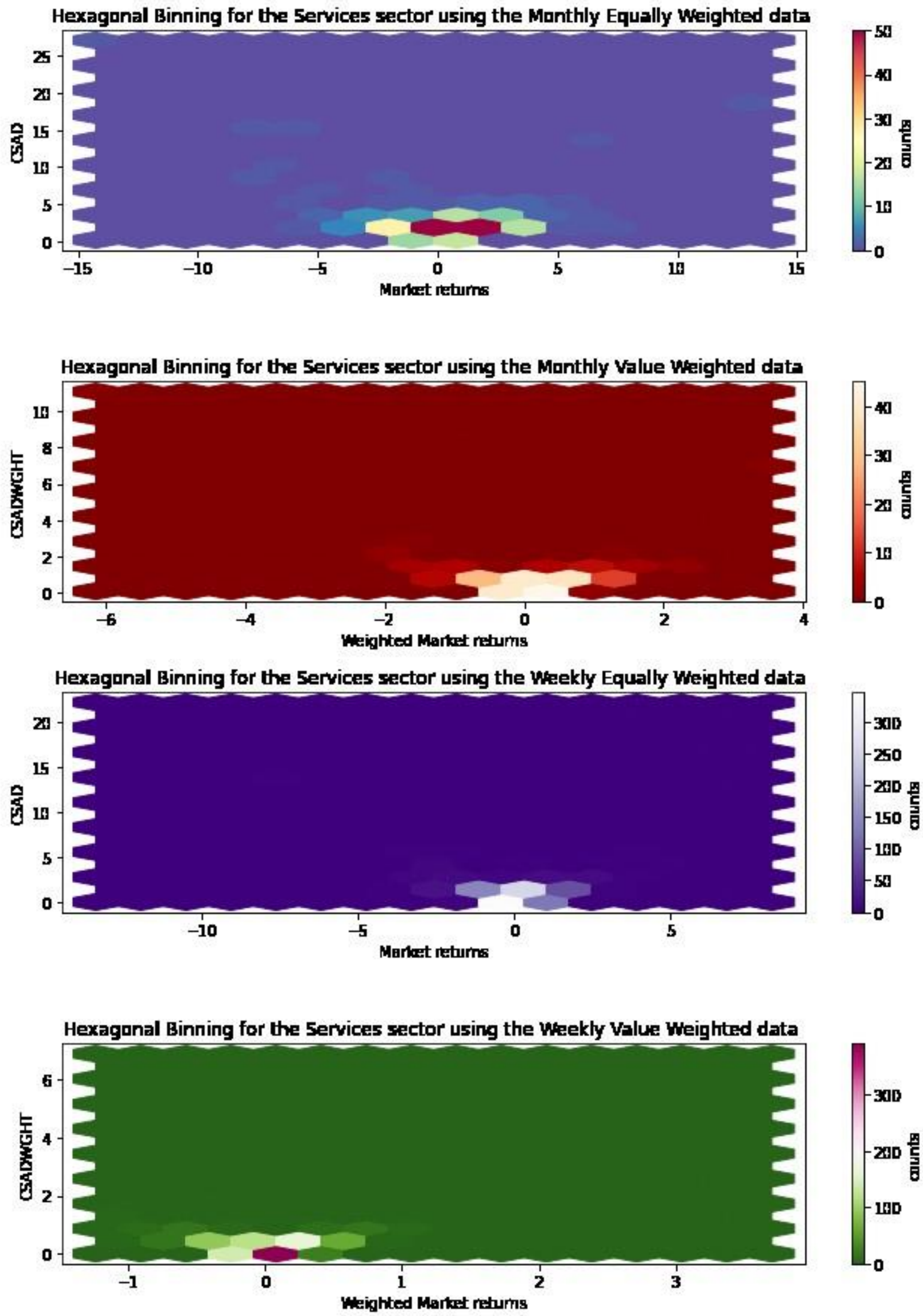
Source: Python results (2024)

Figure 4.3: Hexagonal binning showing distributive properties of cross-sectional absolute deviations and Market returns for the Resources Sector



Source: Python results (2024)

Figure 4.4: Hexagonal binning showing distributive properties of cross-sectional absolute deviations and Market returns for the Services Sector



Source: Python results (2024)

4.4.2 Herding behaviour results based on the static approach

The results of the static models are presented in Table 4.6 and Table 4.7. The static model results reveal absence of herding evidence for the all the sectors as shown by positive and negative but insignificant coefficients φ_2 save for the Industrials sector using the value weighted weekly data. Thus, the return dispersion as proxied by the equally and value weighted cross sectional absolute deviation increases with the absolute market returns for all the sectors save for the Industrials sector. This finding corroborates with Elshqirat (2019) but in contrast to Guney *et al*. (2017) for the NSX. Guney *et al.* (2017) find evidence of herding behaviour for the whole market employing the daily data in contrast to this study that employs the weekly and monthly data. Noteworthy from Table 4.6 and Table 4.7 is the detection of significant anti or negative herding as evidenced by positive and statistically significant coefficient φ_2.

4.4.3 Herding behaviour under different regimes

Estimates of the two-regime herding models are presented in Table 4.8 through Table 4.11. Besides the likelihood values, the selection criterions such as Akaike Information Criterion (AIC) and Bayes-Schwartz Information Criterion (BIC) are also calculated to provide a trade-off between parsimony and goodness of fit of the model. The Markov Regime Switching Models (MRSM) in Table 4.8 through 4.11 indicate that all the sectors have substantially larger log-likelihood and smaller criteria values than their counterpart static models in Table 4.6 and Table 4.7. This shows that the MRSMs are statistically superior to the static models which supports the preference of the former to the later.

Table 4.6: Regression results for the static model using the OLS for the weekly data

Panel A: $CSAD_t = \alpha + \varphi_1 \lvert R_{m,t} \rvert + \varphi_2 R_{m,t}^2 + \varphi_3 CSAD_{t-1} + \varepsilon_t$								
	α	φ_1	φ_2	φ_3	LL	AIC	BIC	Adj. R^2
Financials	0.4121** (13.058)	0.6162** (8.817)	0.1189** (3.223)	0.0882** (2.767)	-336.44	680.9	700.8	0.681
Industrials	0.2498** (6.202)	1.0178** (14.075)	0.0297** (8.089)	0.0424** (2.101)	-1035.1	2078	2098	0.836
Resources	0.7132** (7.674)	0.3188** (2.287)	0.0441 (1.185)	0.1428** (3.640)	-1348.6	2705	2725	0.382
Services	0.3927** (7.332)	0.5598** (6.223)	0.0971** (4.887)	0.0606** (2.263)	-1059.3	2127	2147	0.774
Panel B: $CSADWGHT_t = \alpha + \varphi_1 \lvert RWGHT_{m,t} \rvert + \varphi_2 RWGHT_{m,t}^2 + \varphi_3 CSADWGHT_{t-1} + \varepsilon_t$								
Financials	0.0212** (17.998)	1.0497** (37.908)	0.3890** (3.289)	0.0568** (4.836)	2805.5	-5603	-5583	0.917
Industrials	0.0485** (6.801)	1.2044** (30.886)	-0.0515** (-5.826)	0.0183 (1.101)	674.62	-1341	-1321	0.870
Resources	0.0159 (1.451)	1.3298** (23.930)	-0.0398 (-0.913)	0.0260** (2.580)	530.33	-1053	-1033	0.921
Services	0.1222** (11.052)	0.4711** (5.527)	0.2812** (2.860)	0.0412** (3.808)	553.30	-1099	-1079	0.762

Note: *, ** Indicates significant at the 10%, and 5% level of significance respectively. The numbers in parenthesis are the values of the statistical t-ratios based on the Newey-West consistent estimators. LL denotes log-likelihood of the OLS method, AIC represents the Akaike Information Criterion $=-2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})$. BIC denotes Bayes-Schwartz Information Criterion $=-2\ln L(\widehat{\Theta}) + dim(\widehat{\Theta})\ln T$.

Table 4.7: Regression results for the static model using the OLS for the monthly data

Panel A: $CSAD_t = \alpha + \varphi_1\left|R_{m,t}\right| + \varphi_2 R_{m,t}^2 + \varphi_3 CSAD_{t-1} + \varepsilon_t$								
	α	φ_1	φ_2	φ_3	LL	AIC	BIC	Adj. R^2
Financials	1.1053** (10.284)	0.3353** (3.287)	0.0971** (3.523)	0.1238** (2.747)	-272.53	553.1	567.1	0.669
Industrials	0.8794** (8.144)	0.4221** (4.353)	0.0579** (8.283)	0.2115** (6.706)	-391.12	790.2	804.3	0.760
Resources	2.0522** (8.348)	0.0909 (0.822)	0.0482** (3.653)	0.0536 (1.031)	-481.19	970.4	984.4	0.368
Services	1.5093** (5.192)	0.0518 (0.245)	0.1048** (4.524)	0.0748 (1.346)	-444.45	896.9	910.9	0.689
Panel B: $CSADWGHT_t = \alpha + \varphi_1\left|R_{m,t}\right| + \varphi_2 R_{m,t}^2 + \varphi_3 CSADWGHT_{t-1} + \varepsilon_t$								
Financials	0.0574** (10.974)	0.8278** (15.537)	0.6391** (5.262)	0.0559** (2.543)	491.46	-974.9	-960.9	0.913
Industrials	0.2183** (4.290)	0.9215** (7.071)	0.0241 (0.524)	0.0136 (0.475)	-75.360	158.7	172.7	0.821
Resources	0.1631** (2.894)	1.2161** (12.653)	0.0107 (0.274)	-0.0321 (-1.444)	-70.679	149.4	163.4	0.891
Services	0.2978** (6.284)	0.4240** (4.251)	0.2295** (11.693)	0.0137 (0.506)	-57.870	123.7	137.7	0.875

Note: *, ** Indicates significant at the 10%, and 5% level of significance respectively. The numbers in parenthesis are the values of the statistical t-ratios based on the Newey-West consistent estimators. LL denotes log-likelihood of the OLS method, AIC represents the Akaike Information Criterion $=-2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})$. BIC denotes Bayes-Schwartz Information Criterion $=-2\ln L(\widehat{\Theta}) + dim(\widehat{\Theta})\ln T$.

Table 4.8: Regime switching model results using the equally weighted weekly data.

Parameter	Financials	Industrials	Resources	Services
α_1	0.7656**	0.3161**	0.7727**	0.3811**
α_2	0.3725**	0.5343**	1.2509**	0.7122**
δ_{11}	0.7615**	0.6266**	-0.0636	0.4735**
δ_{12}	0.6064**	1.5457**	0.7037**	0.9538**
δ_{21}	0.1185**	0.0511**	0.1266**	0.0271**
δ_{22}	0.0322**	-0.0630**	-0.0382**	0.0570**
δ_{31}	-0.0600	0.0052	0.0477**	0.0144
δ_{32}	0.0575**	-0.0144	0.0153	0.1174**
σ_1	0.1803**	0.0669**	0.2199**	0.0814**
σ_2	0.0345**	0.7609**	0.9938**	0.7302**
p_{11}	0.8222**	0.8751**	0.8879**	0.7930**
p_{22}	0.0626**	0.3663**	0.2305**	0.7438**
τ_1	5.62	8.00	8.91	4.83
τ_2	15.96	2.72	4.33	1.34
n	1077	1077	1077	1077
log L	-90.958	-645.610	-1158.082	-699.323
AIC	205.917	1315.219	2340.164	1422.645
BIC	265.700	1375.002	2399.947	1482.428
HQIC	228.557	1337.859	2362.803	1445.285

Notes: This table presents results of the following two regime Markov switching model:

$CSAD_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}CSAD_{t-1} + \sigma_{s_t}\varepsilon_t$, where$p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$

τ_k denotes the duration of regime k; HQIC denotes Hannan-Quinn Information Criterion =$-2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})\ln T$.

*, ** Indicates statistically significant at 10%, and 5% level respectively.

Table 4.9: Regime switching model results using the value weighted weekly data

Parameter	Financials	Industrials	Resources	Services
α_1	0.0354**	0.0016	0.0045	0.0687**
α_2	0.0189**	0.0620**	0.0821	0.1944**
δ_{11}	1.0556**	1.6703**	1.4219**	0.5443**
δ_{12}	1.0206**	1.1812**	0.9528**	0.5294**
δ_{21}	0.1366	-4.5286**	-0.0437**	0.0357**
δ_{22}	0.5837**	-0.0466**	0.1019**	0.3400**
δ_{31}	0.1639**	-0.0070**	-0.0026	0.0071
δ_{32}	0.0328**	0.0178	0.0851**	0.0307
σ_1	0.0006**	0.0002**	0.0027**	0.0018**
σ_2	0.0001**	0.0182**	0.0977**	0.0188**
p_{11}	0.2153**	0.3700**	0.9880**	0.6516**
p_{22}	0.1711**	0.0892**	0.0527**	0.4581**
τ_1	1.27	1.58	83.57	2.87
τ_2	5.84	11.20	18.96	2.18
n	1077	1077	1077	1077
$\log L$	2970.966	724.713	1252.372	953.994
AIC	-5917.932	-1425.426	-2480.743	-1883.987
BIC	-5858.148	-1365.643	-2420.960	-1824.204
HQIC	-5895.292	-1402.786	-2458.104	-1861.347

Notes: This table presents results of the following two regime Markov switching model:

$CSADWGHT_t = \alpha_{0,s_t} + \delta_{1,s_t}|R_{m,t}| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}CSADWGHT_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$

τ_k denotes the duration of regime k; HQIC denotes Hannan-Quinn Information Criterion $= -2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})\ln T$.

*, ** Indicates statistically significant at 10%, and 5% level respectively.

Table 4.10: Regime switching model results using the equally weighted monthly data

Parameter	Financials	Industrials	Resources	Services
α_1	1.8123**	1.3292**	0.5434**	1.3178**
α_2	1.0338**	1.0259**	2.7071**	2.3738**
δ_{11}	0.5706**	0.0929	0.8978**	0.3661**
δ_{12}	0.3561**	1.2756**	0.0591	1.0271**
δ_{21}	0.0711**	0.0844**	-0.1806**	-0.0189
δ_{22}	0.0510**	-0.0671**	0.0473**	0.0328
δ_{31}	-0.0138	-0.0664	0.0990	0.0452
δ_{32}	0.0447	0.1472**	-0.0046	-0.0254
σ_1	0.7841**	0.3918**	0.1616**	0.5345**
σ_2	0.1163**	1.7271**	3.3244**	5.6640**
p_{11}	0.8391**	0.8751**	0.5281**	0.9042**
p_{22}	0.0796**	0.2088**	0.1663**	0.6578**
τ_1	6.21	8.00	2.11	10.44
τ_2	12.55	4.78	6.01	1.52
n	246	246	246	246
$\log L$	-206.893	-352.382	-461.463	-355.032
AIC	437.785	728.764	946.925	734.064
BIC	479.849	770.828	988.989	776.128
HQIC	454.722	745.702	963.863	751.001

Notes: This table presents results of the following two regime Markov switching model:

$$CSAD_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}CSAD_{t-1} + \sigma_{s_t}\varepsilon_t, \text{ where} p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$$

τ_{k} denotes the duration of regime k; HQIC denotes Hannan-Quinn Information Criterion $=-2\ln L\left(\widehat{\Theta}\right) + 2dim\left(\widehat{\Theta}\right)\ln T$.

*, ** Indicates statistically significant at 10%, and 5% level respectively.

Table 4.11: Regime switching model results using the value weighted monthly data

Parameter	Financials	Industrials	Resources	Services
α_1	0.0551**	0.0565*	-0.0298	0.1744**
α_2	0.0841**	0.3205**	0.3074**	0.3424**
δ_{11}	0.8317**	1.7505	1.8571**	0.4494**
δ_{12}	0.7540**	0.8593**	1.1130**	0.5700**
δ_{21}	0.6487**	-1.1035**	-0.5860**	0.0657*
δ_{22}	0.6221	0.0321*	0.0286	0.2055**
δ_{31}	0.0210	-0.0171	-0.0284**	-0.0074
δ_{32}	0.2162	0.0055	-0.0328	0.0296
σ_1	0.0005**	0.0084**	0.0052**	0.0052**
σ_2	0.0017**	0.1525**	0.1538**	0.0978**
p_{11}	0.8654**	0.6361**	0.5594**	0.6606**
p_{22}	0.8802**	0.2231**	0.3191**	0.2184**
τ_1	7.42	2.74	2.26	2.94
τ_2	1.13	4.48	3.13	4.57
n	246	246	246	246
log L	521.141	-44.070	-23.330	0.593
AIC	-1018.282	112.140	70.661	22.814
BIC	-976.218	154.204	112.725	64.878
HQIC	-1001.345	129.077	87.598	39.751

Notes: This table presents results of the following two regime Markov switching model:

$CSADWGHT_t = \alpha_{0,s_t} + \delta_{1,s_t}|R_{m,t}| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}CSADWGHT_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$

τ_k denotes the duration of regime k; HQIC denotes Hannan-Quinn Information Criterion $= -2\ln L(\widehat{\Theta}) + 2dim(\widehat{\Theta})\ln T$.

*, ** Indicates statistically significant at 10%, and 5% level respectively.

Results in Table 4.8 through Table 4.11 show that the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for all the sectors save for the Financials sector. Thus $\hat{\sigma}_2$ corresponds to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime (tranquil regimes) except for the financials sector. In all the sectors the state transition probabilities are statistically significant which indicates stability of the hidden market regimes inferred from the models and have tendency of remaining in the current regimes. The transition probability of switching from high volatility regime to a low one is estimated as $1 - \hat{p}_{22}$, whereas the transition probability from low volatility state to a high one is estimated as $1 - \hat{p}_{11}$. In this regard, using the equally weighted weekly data, the transition probabilities of moving from a high volatility to a low volatility are: 0.6337, 0.7695, and 0.2562 for Industrial, Resource and Service sectors respectively. The transition probabilities of moving from a low volatility state to a high one are: 0.1249, 0.1121, and 0.207 for Industrial, Resource and Service sectors respectively. However, for the financial sector, the volatility estimator $\hat{\sigma}_1$ is greater than volatility estimator $\hat{\sigma}_2$. Thus, Regime 1 corresponds to high volatility regime while Regime 2 corresponds to low volatility regime. The transition probability of switching from high volatility regime to a low one is estimated as $1 - \hat{p}_{11} = 0.1778$, whereas the transition probability from low volatility state to a high one is estimated as $1 - \hat{p}_{12} = 0.9374$.

Using the value weighted weekly data in Table 4.9, the transition probabilities of moving from a high volatility to a low volatility are: 0.9108, 0.9473, and 0.5419 for Industrial, Resource and Service sectors respectively. The transition probabilities of moving from a low volatility state to a high one are: 0.6300, 0.012, and 0.3484 for Industrial, Resource, and Service sectors respectively. However, for the financial sector, the volatility estimator $\hat{\sigma}_1$ is greater than volatility estimator $\hat{\sigma}_2$. Thus, Regime 1 corresponds to high volatility regime while Regime 2 corresponds to low volatility regime. The transition probability of switching from high volatility regime to a low one is estimated as $1 - \hat{p}_{11} = 0.7847$, whereas the transition probability from low volatility state to a high one is estimated as $1 - \hat{p}_{12} = 0.8289$.

From the equally weighted monthly data in Table 4.10, the transition probabilities of moving from a high volatility to a low volatility are: 0.7912, 0.8337, and 0.3422 for Industrial, Resource and Service sectors respectively. The transition probabilities of moving from a low volatility state to a high one are: 0.1249, 0.4719, and 0.0958 for Industrial, Resource, and Service sectors respectively. However, for the financial sector, the volatility estimator $\hat{\sigma}_1$ is greater than volatility estimator$\hat{\sigma}_2$. Thus, Regime 1 corresponds to high volatility regime while Regime 2 corresponds to low volatility regime. The transition probability of switching from high volatility regime to a low one is estimated as $1 - \hat{p}_{11} = 0.1609$, whereas the transition probability from low volatility state to a high one is estimated as $1 - \hat{p}_{12} = 0.9204$.

From the value weighted monthly data in Table 4.11, the transition probabilities of moving from a high volatility to a low volatility are: 0.1198, 0.7769, 0.6809, and 0.7816 for the financial, industrial, resource and service sectors respectively. The transition probabilities of moving from a low volatility state to a high one are: 0.1346, 0.3639, 0.4406, and 0.3394 for the financial, industrial, resource, and service sectors respectively.

Besides volatility clustering, the transition probabilities above also reflects that the high volatility state is less persistent and stable than the low volatility state. Besides, the non-diagonal elements of the transition probability matrices are much less than their diagonal counterparts suggesting the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 4.8, the Industrial and Resource sectors exhibit herding behaviour under the high volatility regime. This is also consistent with findings by Babalos *et al.* (2015), Cakan and Balagyozyan (2016), Ahmed *et al.* (2019), Fu and Wu (2020), and Mand and Sifat (2021). A possible explanation of this findings is that investors tend to discard their own convictions and mimic others' actions during high volatility than during the tranquil one. From Table 4.9, novel evidence of sectoral herding behaviour is detected in the Industrial and Resource sectors although under the low volatility regime. From Table 4.10, herding behaviour is detected under Industrials sector under both the low and high volatile regime, while for the resource sectors is detected under the low regime. Furthermore, in Table 4.11 herding behaviour is detected in the Industrial and Resource sectors under the low volatility regimes. Noteworthy observation from this study is that the static model is unable to capture herding behaviour during times of market stress unlike the regime switching model which is also in line with previous studies like Christie and Huang (1995) and Chang *et al.* (2000).

Table 4.8 through 4.11 also provides expected durations of the market regimes. From Table 4.8, the high volatility regime tend to the most persistent one as indicated by the longest average regime duration under the financials sector similar to finding by Balcilar and Demirer (2015). The average regime duration for the high volatility regimes ranges from 1.34 weeks for the Services to 15.96 for the financial sector. This underscores the significance of hedging instruments to cushion volatility in the financial sector. The shortest regime duration is reported in the Services sector, implying more frequent regime switching in this sector. This also implies that this sector is the most volatile sector relative to other sectors.

From Table 4.9, the low volatility regimes are most persistent in the resource and service sectors as indicated by the average regime durations while the high volatility regimes are most persistent in the financial and industrial sectors. The average regime duration for the low volatility state ranges from 1.27 for the financials to 83.57 weeks for the resources. For the high volatility regime, the longest average regime durations are observed in the Industrial and Resources sectors. This finding underscores the significance of hedging instruments to cushion volatility in the Industrial and resource sectors. The shortest regime durations are reported under the financial and service sectors for the high volatility regimes, implying more frequent state switch in these sectors. This also implies these sectors are the most volatile sectors relative to other sectors.

From Table 4.10, the low volatility regime is most persistent in the industrial and service sectors as indicated by the average regime durations while the high volatility regime is most persistent in the financial and resource sectors. The average regime duration for the low volatility state ranges from 2.11 months for the resources to 10.44 for the Services sector. For the high volatility regime, the longest average regime durations are observed in the Financial and Resource sectors. This also underscores the significance of hedging instruments to cushion volatility in the financial and resource sectors. The shortest regime durations are reported under the industrial and services sector for the high volatility regime, implying more frequent state switch in these sectors. This also implies these sectors are the most volatile sectors relative to other sectors.

From Table 4.11, the high volatility tend to be the most persistent regime as indicated by the longest average regime duration for all the sectors save for the financial sector. The average regime duration for the high volatility regimes ranges from 1.13 months for the Financials sector to 4.57 for the services sector. This underscores the significance of hedging instruments to cushion volatility in these sectors. The shortest regime durations is reported in the financials sector, implying more frequent regime switching in this sector. This also implies that this sector is the most volatile sector relative to other sectors under high volatility regime.

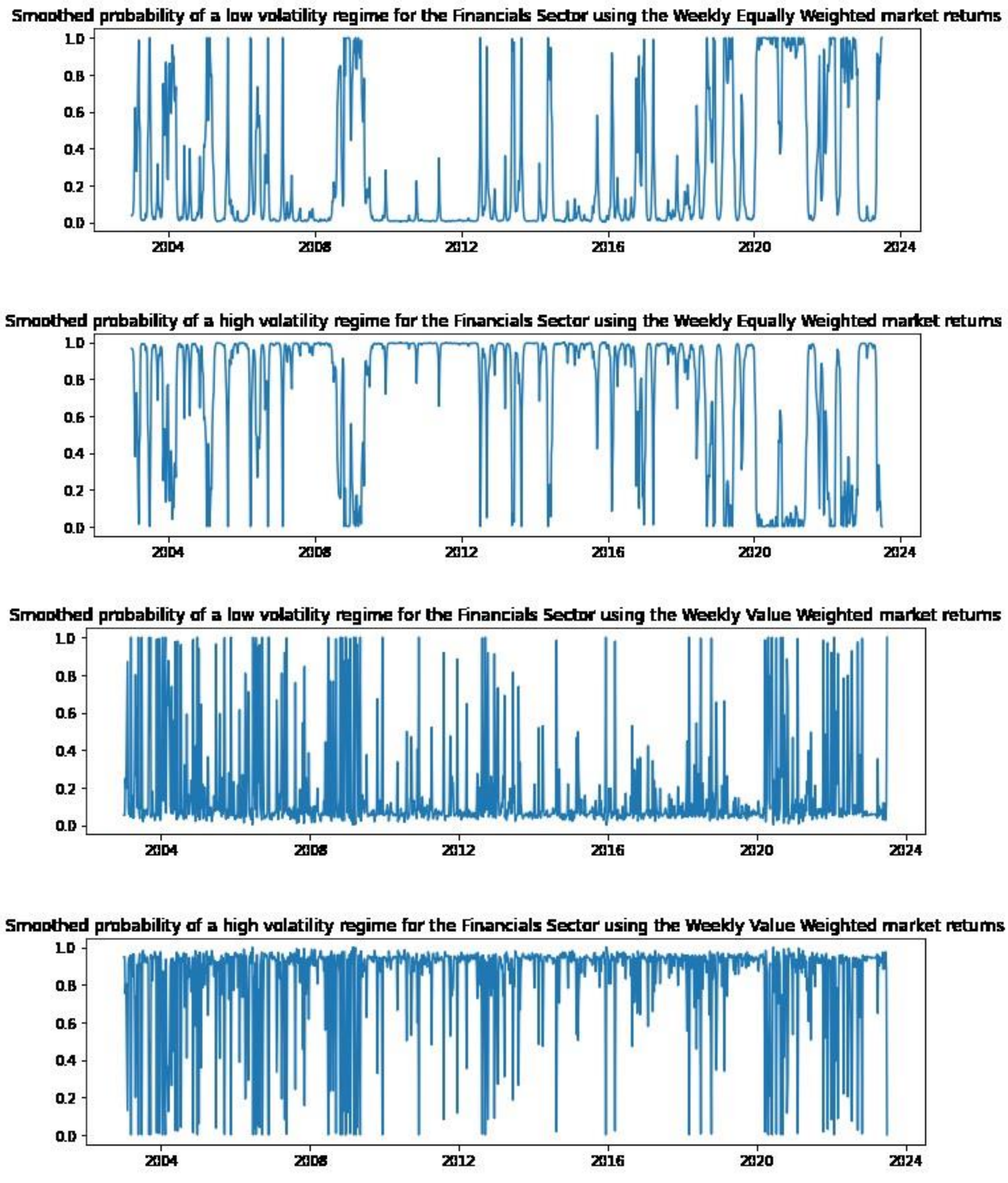
Figures 4.5 through 4.12 show the smoothed probability plots for visual inspection of the dynamic nature of the state transitions and herding behaviour for the various sectors. On a general note, the smoothed probability plots suggest existence of the herding behaviour during the 2008-09 Global Financial Crisis period. The smoothed probability plots in Figures 4.5 through 4.12 tend to suggest a low-high (LH) volatility transition order in which the high volatility regimes follows the low volatility regimes. In this regard, the low-volatility regimes plays as a major role in giving warning to the financial market regulators before the high volatility regime. Furthermore, the smoothed probability regimes between the low and high volatility regimes suggest a bi-directional transitions.

In this regard, financial market regulators can play a pivotal role during uncertainties periods in avoiding possible transitions to high volatility regimes.

4.5 Conclusions and policy implications

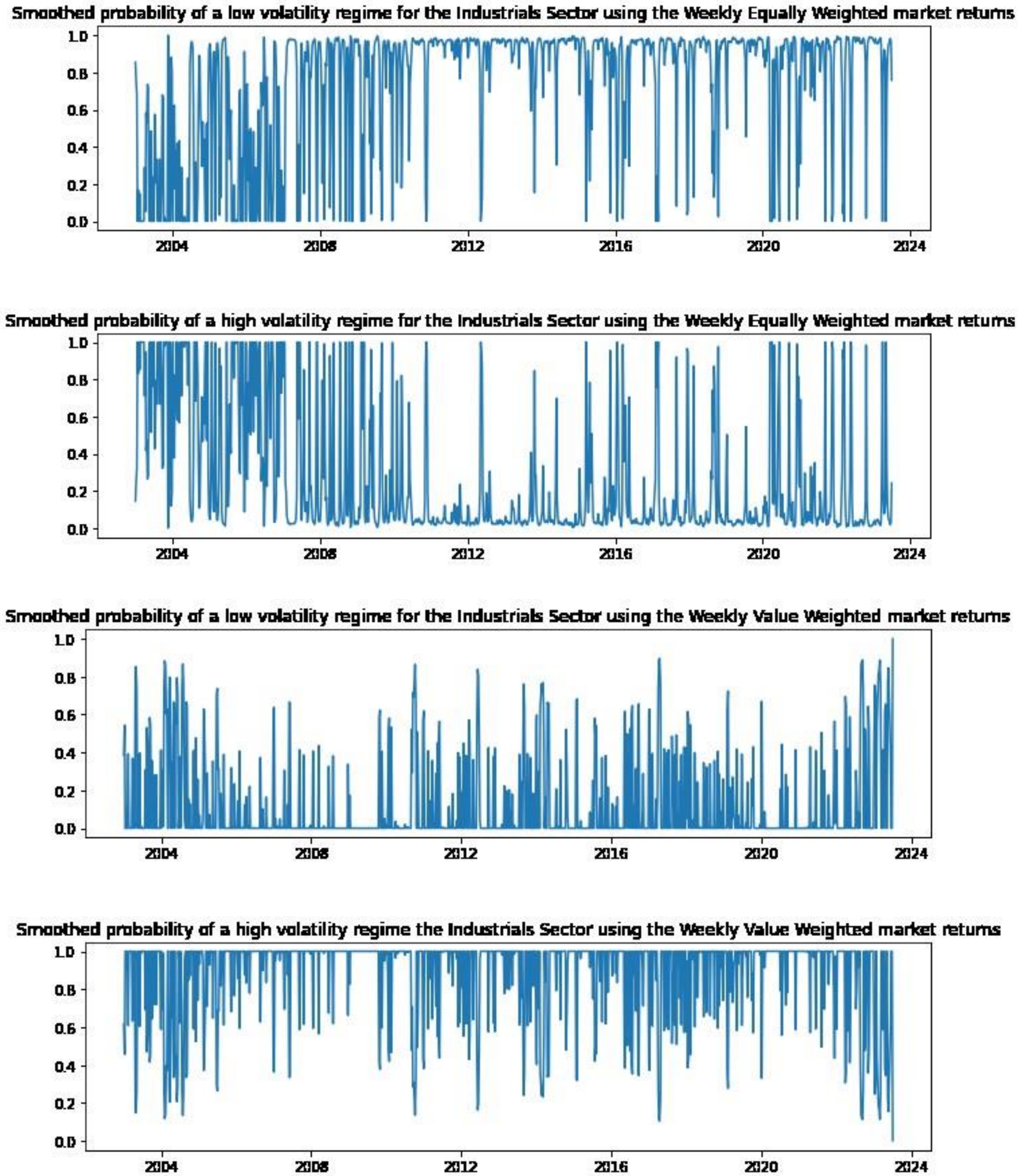
This research examines the existence of sectoral herding behaviour in the NSX employing both the static models and dynamic models. This study found inconsistent and conflicting results emanating from the two models. Based on the weekly and monthly data, the results of the static model reveal evidence of absence of herding behaviour at sectoral level save for the Industrials sector using value weighted weekly data. However, the results of the two-state Markov switching-regime approach revealed non-linearity and existence of herding behaviour for the Industrial and Resource sectors especially during high volatility regime. The finding in this study implies that investors follow their own personal beliefs in tranquil regimes, but follow the actions of others during the more volatile regimes. In this regard, it is better to come up with a larger investment portfolio in order to reach the same diversification goal in more volatile states. Advancing literature on herding behaviour in the emerging markets, this study recommends future researchers to consider using high frequency data such as the daily data since herding behaviour is considered by many to a short to medium term phenomenon.

Figure 4.5: Smoothed probabilities for the Financials Sector using the weekly data



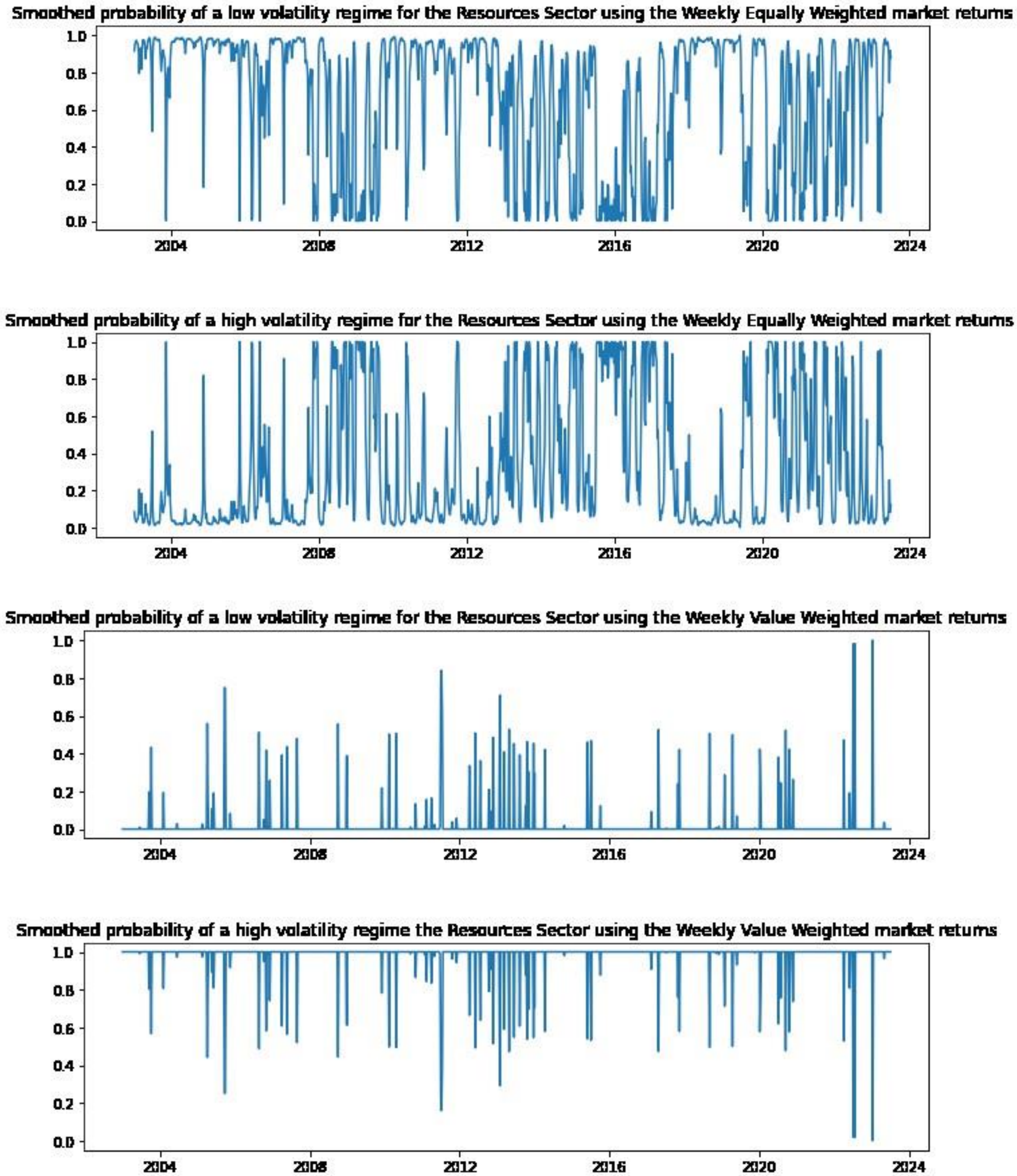
Source: Python results (2024)

Figure 4.6: Smoothed probabilities for the Industrials Sector using the weekly data



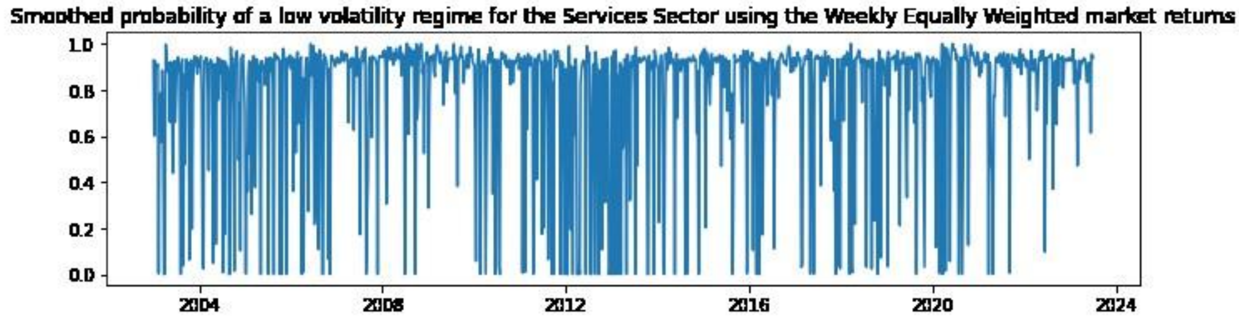
Source: Python results (2024)

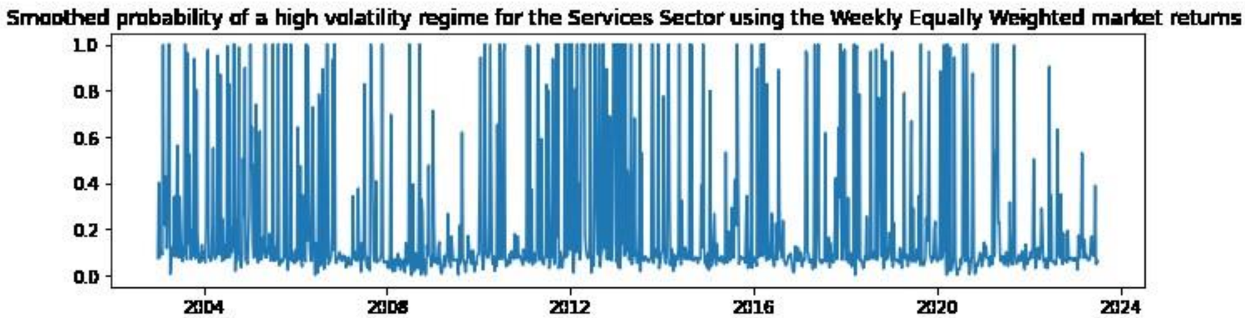
Figure 4.7: Smoothed probabilities for the Resources Sector using the weekly data

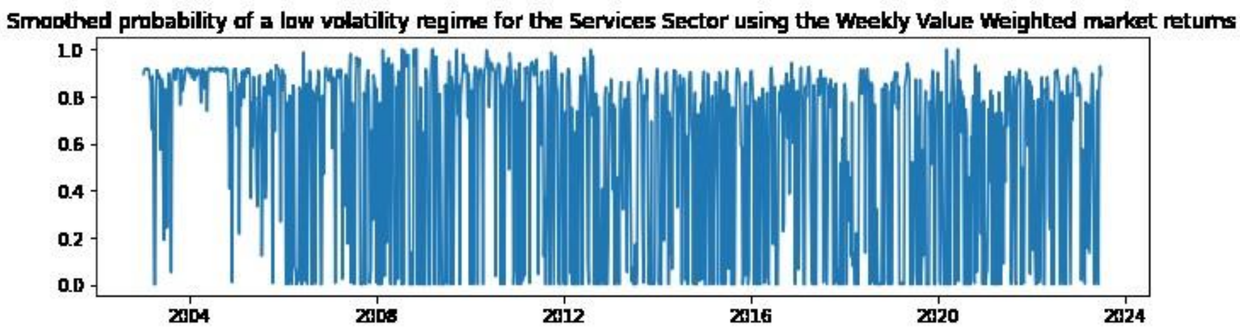


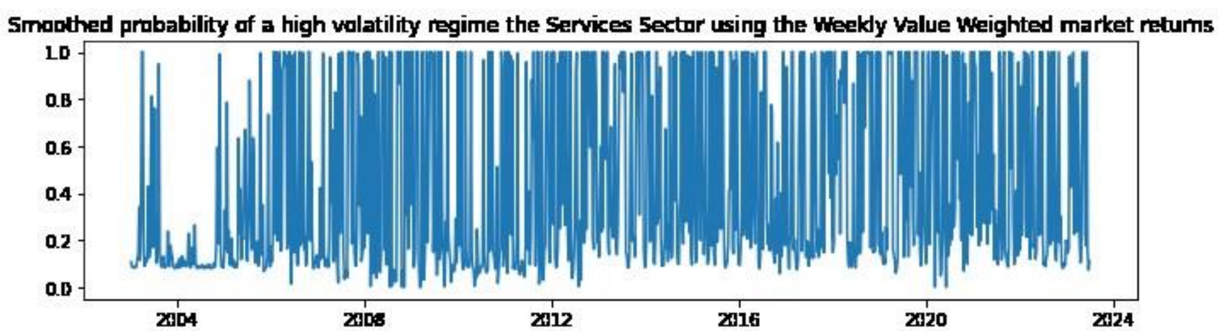
Source: Python results (2024)

Figure 4.8: Smoothed probabilities for the Services Sector using the weekly data



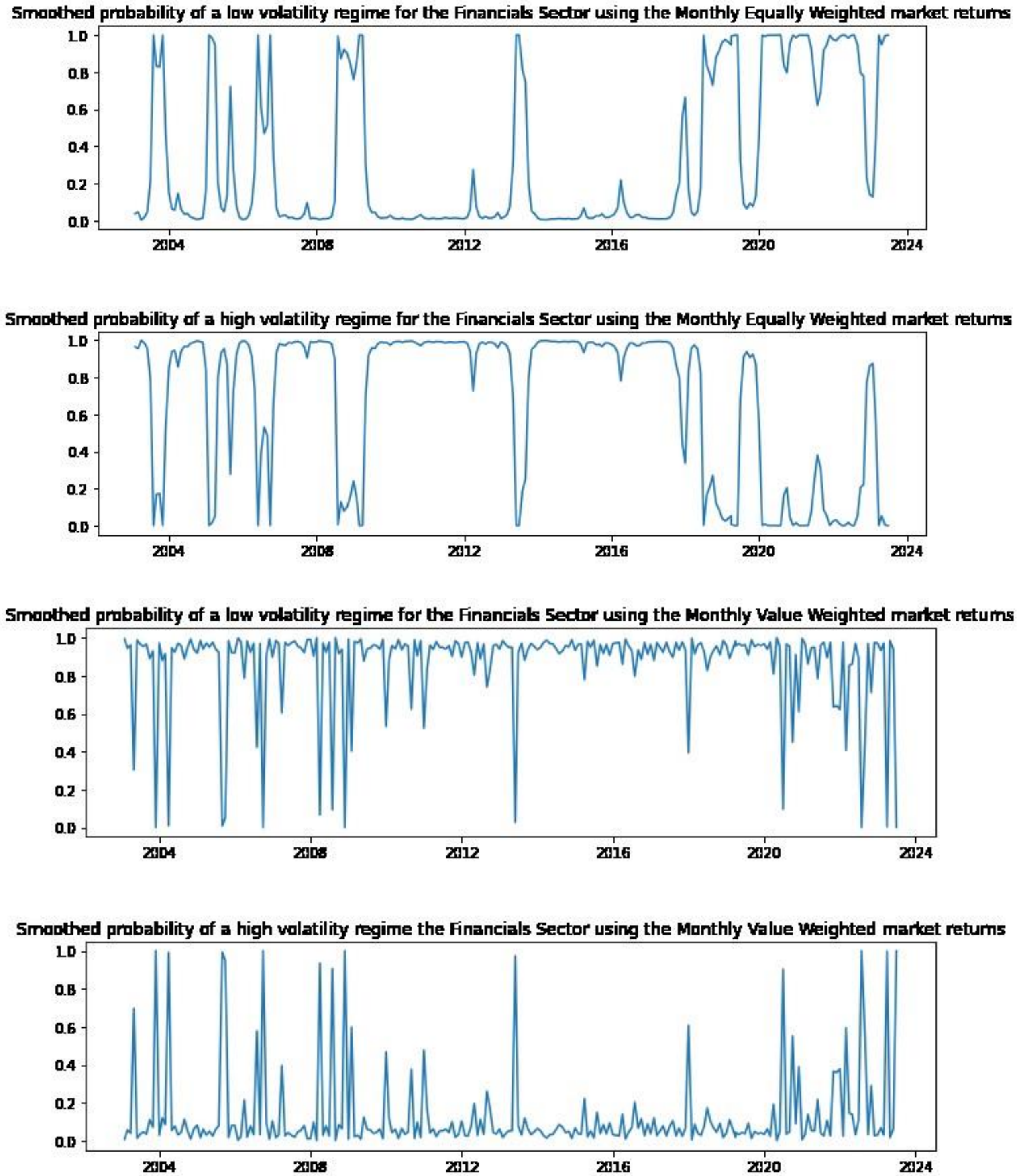






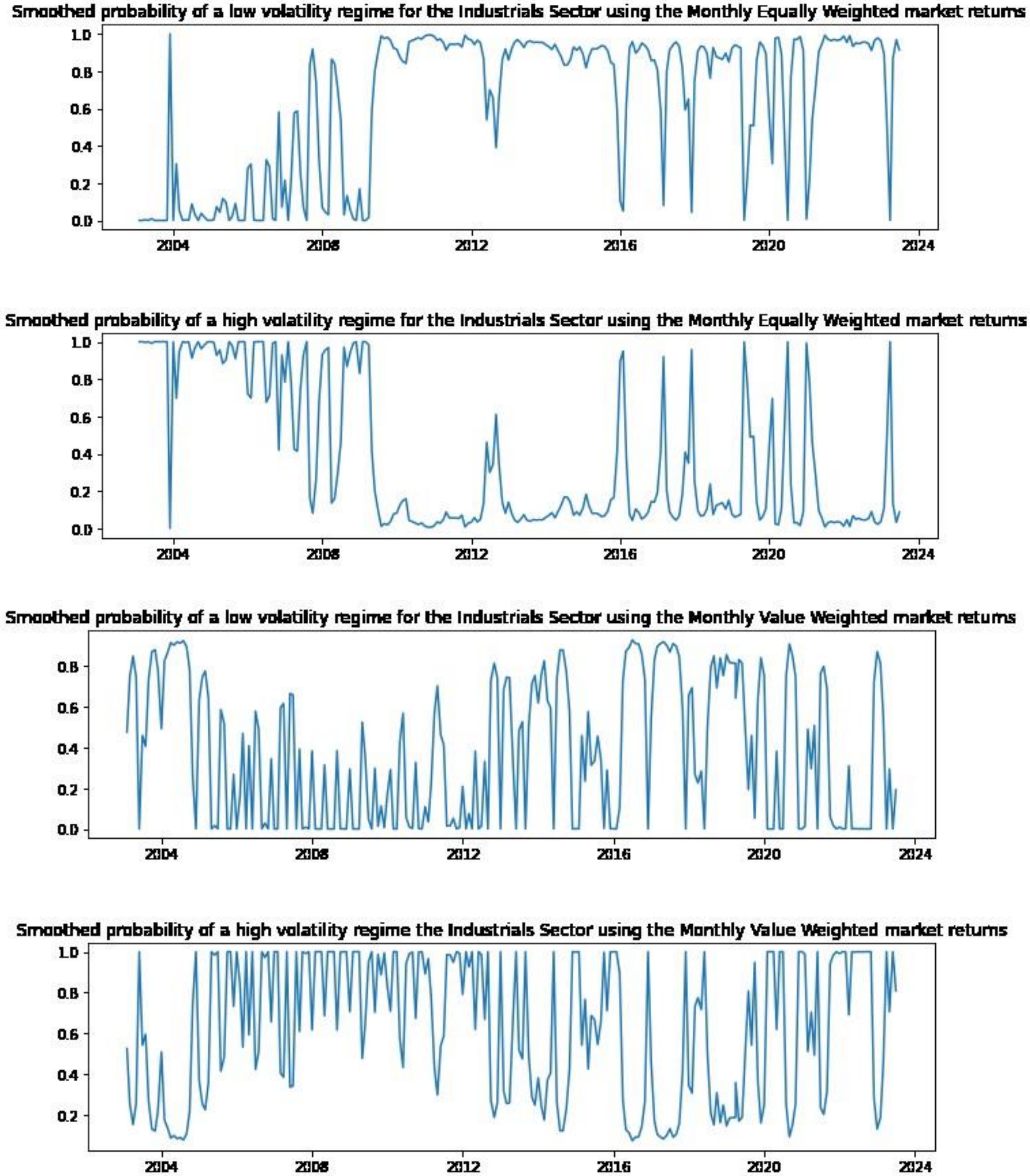
Source: Python results (2024)

Figure 4.9: Smoothed probabilities for the Financials sector using the monthly data



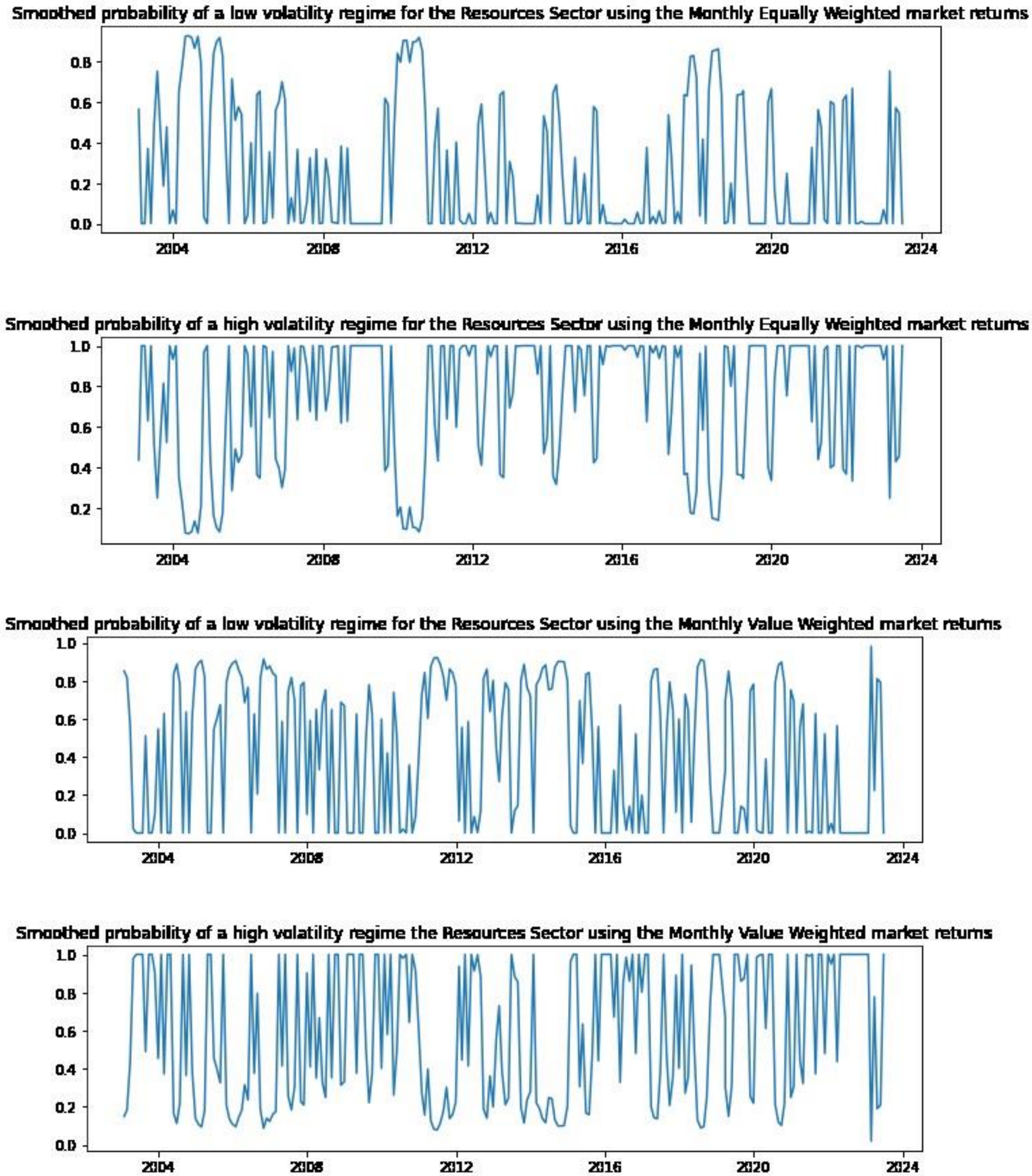
Source: Python results (2024)

Figure 4.10: Smoothed probabilities for the Industrials sector using the monthly data



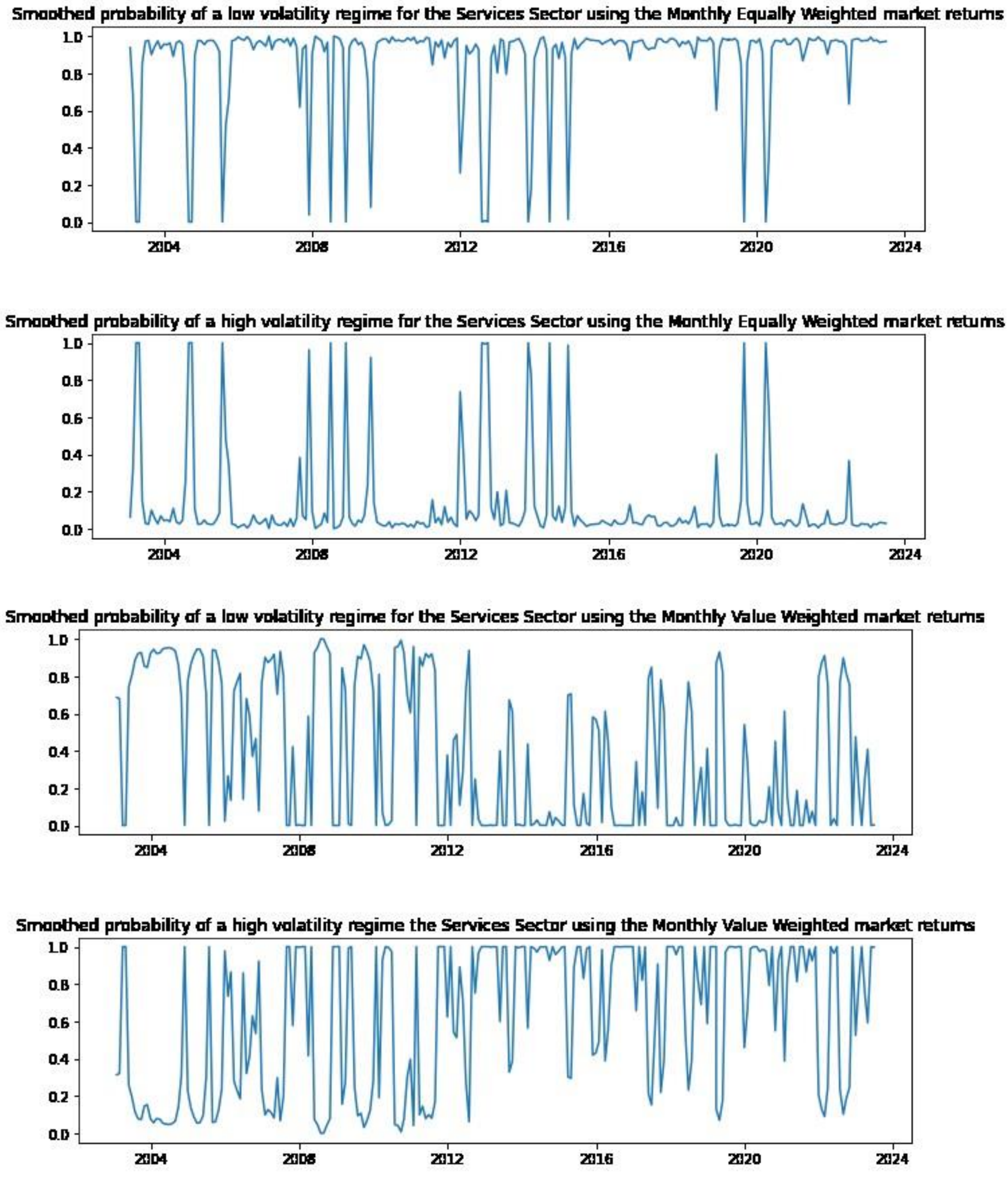
Source: Python results (2024)

Figure 4.11: Smoothed probabilities for the Resources sector using the monthly data



Source: Python results (2024)

Figure 4.12: Smoothed probabilities for the Services sector using the monthly data



Source: Python results (2024)

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Chapter 5: The impact of the South African macroeconomic fluctuations on the herding behaviour in the Namibian Securities Exchange (NSX): A Markov Regime Switching Approach

Abstract

This study examines the influence of variations in South African interest rates and exchange rates on herd behaviour in the Namibian Securities Exchange (NSX) using the time-varying transition probability Markov regime- switching model for the period 1st January 2003 to 30th June 2023. The results of the 2-regime Markov switching model revealed mixed results regarding the influence of interest rates and exchange rate variations on herding behaviour in the NSX. Herding behaviour is found when all equity stocks are considered and for the Industrial and Service sectors. Results of interest rates as proxied by the Johannesburg Interbank Average Rate (JIBAR) 3 month yield rate reveal positive (negative) effect on herding behaviour for the entire market and all the sectors. The exchange rate as proxied by the United States Dollar (USD) to South African Rand as well as extreme changes in ZAR, is also found to have both positive and negative effect on herding behaviour in the NSX. Thus, Namibian policymakers should strengthen communications and coordination with the financial market regulators as changes in macroeconomic policies like interest rates and exchanges leads to herding behaviour in the entire market and the sectors.

Key words:

Exchange rate, Herding behaviour, Interest rate, and Markov Regime-Switching model

5.1 Introduction

In examining how investors in a domestic stock market respond to unexpected external shocks, most previous studies assumed herding behaviour to be a non-time varying element. However, this may not necessarily be true because after getting new information, market participants may not react immediately, but rather change their investment behaviour in future periods, as pointed by Yang and Chen (2015). Exchange rates and interest rates are two key macroeconomic variables which affect herd behaviour in a stock market. Discount rate mechanisms, equity premiums and expected future dividends are some of the ways in which interest rate as an element of monetary policy formulated by the central bank affects prices of stocks (Gong & Dai, 2017). In addition to the capital inflows and outflows of the country, variations in foreign exchange rates affect cash flows and competitiveness of businesses which in turn affect the stock prices. Although some notable previous studies like Balcilar and Demirer (2015), Lee *et al*. (2015), Gong and Dai (2017) and Rahman and Wati (2020) among others tried to explore the influence of external macroeconomic shocks on domestic stock market in emerging markets, the area remain largely unexplored especially in African context especially the Namibian Securities Exchange (NSX). This is one major contribution of this current study. The NSX is highly integrated to the Johannesburg Stock Exchange (JSE) with a number of stocks being dually listed on these two stock markets. Furthermore, the Namibian dollar (NAD) is pegged with the South African Rand (ZAR) at a ratio of 1 NAD to 1 ZAR at par. In this regard, changes in South Africa policy regarding interest rates and exchange rates is expected to have an influence on the performance of the NSX whether directly or indirectly. Apart from this, this current study went a step further in examining the influence of extreme foreign exchange volatility on herd behaviour considering such is likely to elicit public investment behaviour. Furthermore, this study distinguishes itself from previous studies by employing the time-varying transition probability Markov Regime switching model to examine the influence of variations in interest rates and foreign exchange rates on herd behaviour. The Markov Regime switching model is preferred in this study to the static model, due to its ability to capture time-varying nature of herd behaviour as pointed by Yang and Chen (2015). The rest of this study is structured as follows: section 5.2 highlights literature on the effects of variations in interest rates and exchange rates on herd behaviour, section 5.3 presents the methodology, section 5.4 presents and discusses the empirical results and section 5.5 concludes the study.

5.2 Literature review

This section highlights the conceptual framework regarding the effects of variations interest rates and exchange rates on herding behaviour which forms the basis for the hypothesis of this study. Herding behaviour refers to a tendency by market participants to follow or imitate the actions of others, particularly during periods of market uncertainties. The dominance of large investors or institutional investors in a market makes herd behaviour increasing important as their performance is generally evaluated against that of other institutional investors as pointed by Chang *et al*. (2000). Herd behaviour tend to occur more often during times of market stress or uncertainties due to fear and panic. In such situations, market participants tend to disregard their own investment beliefs and follow the decisions of others (Christie & Huang, 1995). Herding tend to occur more often in emerging markets due to opportunities to make abnormal profits unlike in developed markets, asymmetric information, lack of transparency and disclosure regarding information as well as poor regulatory mechanism of financial markets (Rahman & Wati, 2020).

As mentioned above, the monetary policy formulated by the central bank plays a pivotal role in stock prices changes. For instance, an unexpected increase in interest rates causes decrease in stock prices due to the role it plays in anticipated future dividends, discount rate mechanisms and equity premium (Gong & Dai, 2017). By contrast, there is no clear cut relationship between changes in foreign exchange and stock returns. For instance, the depreciation of local currency may improve international competitiveness of local business and boost their profits thereby benefiting the prices of the stocks. Hau and Rey (2006) averred that the desire to hedge foreign exchange risk and rebalancing of foreign equity portfolio by investors as a result of a gain may lead to the depreciation of pertinent foreign currency. This may also lead to a negative relationship between currency and stock returns. However, the correlation between exchange rates and stock returns tend to differ between developing and advanced stock markets as result of different capital inflows and outflows as well as varying global stock market conditions (Cho *et al.*, 2016). Thus, capital account tend to be the reference point of the relationship between currency and stock returns which supports the inkling of capital flows. Turmoil or downturn in the global stock markets usually leads to capital outflows from the emerging markets into the advanced markets. In this situation, there tend to be positive correlation between currency return and equity returns in developing markets and a negative correlation in advanced stock markets. Similar correlations holds when global stock market is up. Appreciation of local currency is generally viewed as "good" news and beneficial to the developing markets as a result of cash inflows into these markets, whereas depreciation of local currency is considered as "bad" news (Gong & Dai, 2017).

A number of empirical studies have been carried so far particularly to examine the influence of exchange rates and interest rates on herding behaviour in emerging and developed stock markets. Some of the notable studies are summarized in Table 5.1 below. From the Asian perspective Rahman and Wati (2020) find herding behaviour to be influenced by changes in interest rates employing OLS and the Chang *et al.* (2000) herding measure. This finding also corroborates with the finding by Gong and Dai (2017) and Lee *et al*. (2015). However, Lee *et al.* (2015) find mixed results regarding interest rate for the Taiwan stock market with the results revealing stronger herding effect of low interest rates than high interest rates at low quantiles and vice versa at median to high quantiles. In terms of exchange rates, Gong and Dai (2017) finds herd behaviour to be driven by Chinese currency depreciation. Furthermore, the results by Gong and Dai (2017) reveal 1% CNY depreciation induces herding behaviour whereas 1% CNY does not induce herding behaviour in the Chinese stock market. Despite the effort so far, literature on the effects of interest rates and exchange rates remain limited on the African context particularly the NSX which is major contribution of this study.

Table 5.1: Summary of the empirical studies on the effect of macroeconomic variables (interest rates and exchange rates) on herding behaviour in the stock market

Country	Authors	Period	Methodology	Conclusion
ASEAN-5 (Indonesia, Singapore, Malaysia, the Philippines and Thailand)	Rahman and Wati (2020)	Daily closing prices from January 2000 to December 2018	OLS employing the modified CCK herding measure	The study found herd behaviour to be significantly induced by changes in policy rates as proxied by interest rates in the Indonesia and Thailand stock markets.
China	Gong and Dai (2017)	Daily stock prices from July 2005 to June 2016	OLS employing the modified CCK herding measure	The study indicated herding behaviour to be induced by interest rate increase and Chinese currency (CNY) depreciation. The empirical results also reveal 1% CNY depreciation induces herding behaviour whereas 1% CNY does not induce herding behaviour in the Chinese stock market.
Greater China Stock Markets (China, Hong Kong and Taiwan)	Yang and Chen (2015)	Daily data from January 2005 to December 2009	Kalman-Filter based model and VAR model employing CCK herding measure	The results adduced that weaker responses of herding in the Greater China stock market to U.S. market factors compared to domestic market factors. Market participants in the Chinese and Taiwan stock markets tended to herd with the increasing domestic market returns.
Iran	Jafari *et al*. (2020)	Monthly data from 2008-2018	GARCH employing the CH, CCK and HS herding measures	The study indicated mixed results on the effect of macroeconomic variables on herding behaviour in different industries during the bearish and bullish markets. The study found significant positive relationship between exchange rate growth and herding behaviour among Petroleum Products, Coke and Nuclear Fuel industries during decreasing market conditions (bearish)

				but negative and insignificant during increasing market (bullish). Changes in monetary policy (liquidity growth) was also found to have significant positive effect on herd behaviour under bearish market among Petroleum Products, Coke and Nuclear Fuel industries but insignificant during bullish market conditions for the same industries.
Taiwan	Lee *et al*. (2015)	Daily stock returns from January 2000 to December 2012	Quantile Regression Analysis employing the CH and CCK herding measure	The study produces mixed results on the relationship between changes in exchange rates and interest rates and herding behaviour in the Taiwan Stock Exchange. The results of the Quantile regression demonstrated a positive (negative) relationship between cross-sectional return dispersion and interest rate change during all quantiles. The results also adduced a stronger herding effect of low interest rates than high interest rates at low quantiles and vice versa at median to high quantiles. The results of changes in exchange rates also revealed significant asymmetric herding effect at median quantiles.
Turkey	Balcilar and Demirer (2015)	Daily closing prices from January 2000 to March 2012	Time-varying transition probability Markov Switching model employing the CCK herding measure	The results averred that regime transition probabilities are time varying instead of being constant across periods. The results revealed that global factors such as foreign exchange have heterogeneous effect of regime transitions for other industries except for industrials where global factors are found to be insignificant in driving herd behaviour.

Note: OLS, GARCH, CH, CCK, HS refers to Ordinary Least Squares, Generalised autoregressive conditional heteroscedasticity, Christie and Huang, Chang, Cheng and Khorana, Hwang and Salmon respectively.

5.3 Methodology and data

5.3.1 Static approach to herd behaviour

This study adopts the herding behaviour method proposed by Chang *et al.* (2000) and later modified by Gong and Dai (2017) with some adjustments as follows:

$$Dispersion_t = \alpha_0 + \delta_1\left|R_{m,t}\right| + \delta_2 R_{m,t}^2 + \delta_3 \Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_4 \Delta int_t \left(1 - Dum_{t,1}\right) R_{m,t}^2 + \delta_5 \Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_6 \Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_7 DumApp_t R_{m,t}^2 + \delta_8 DumDep_t R_{m,t}^2 + \delta_9 Dispersion_{t-1} + \varepsilon_t \tag{5.1}$$

Where: Δexc_t and Δint_t denotes changes in exchange rate and changes in interest rates respectively. $Dispersion_t$ is the general notation which represents both the equally (CSAD) and value weighted cross sectional absolute deviation (CSADWGHT) as explained in the previous chapters. The major thrust of this study is to determine whether fluctuations in South African exchange rate and interest rates have an impact on herding behaviour on the NSX. These variables are considered in this study given that the Namibian dollar (NAD) is pegged at 1:1 against the South African Rand (ZAR). Furthermore, the NSX and Johannesburg Stock Exchange (JSE) are intertwined and interdependent considering that a number of stocks are dually listed on these two stock markets. This means any changes in South African macroeconomic policies regarding interest rates and exchange rates is likely to have a direct or indirect effect on the Namibian economy and Namibia financial markets. This study adopts the Johannesburg Interbank Average Rate (JIBAR) 3 month yield rate to measure interest rate. The exchange rate is proxied by United States Dollar (USD) to South African Rand (ZAR).

Thus, $\Delta exc_t > 0$ indicates ZAR depreciation, and vice versa. $Dum_{t,1}$ denotes a dummy variable which is equal to one (1) in the case of interest rate increase (Δint_t) on time t and zero (0) otherwise. $Dum_{t,2}$ denotes a dummy variable which is equal to one (1) in the case of ZAR appreciation $(\Delta exc_t < 0)$ on time t and zero (0) otherwise. $DumDep_t$ is a dummy variable equal to one (1) when Δexc_t lies in the extreme 1% upper tail of the whole Δexc_t distribution (ZAR depreciation) and zero (0) otherwise. $DumApp_t$ is a dummy variable equal to one (1) when Δexc_t lies in the extreme 1% lower tail of the whole Δexc_t distribution (ZAR appreciation) and zero (0) otherwise.

The partial effect of $\Delta R^2_{m,t}$ on $\Delta CSAD_t$ in Equation (5.1) above is thus:

$$\frac{\partial Dispersion_t}{\partial R^2_t} = \delta_2 + \delta_3 \Delta int_t Dum_{t,1} + \delta_4 \Delta int_t \left(1 - Dum_{t,1}\right) + \delta_5 \Delta exc_t Dum_{t,2} + \delta_6 \Delta exc_t (1 - Dum_{t,2}) + \delta_7 DumApp_t + \delta_8 DumDep_t + \delta_9 Dispersion_{t-1} + \varepsilon_t \qquad (5.2)$$

For emerging markets like Namibia, the increase in interest rates and the depreciation of ZAR usually are assumed to dampens the appeal of the stock equities and vice versa. Thus, increase in interest rates and depreciation of ZAR are assumed to induce herding behaviour as they are regarded as bad news in the equities markets. If this is true, then δ_3 and δ_6 will be significantly negative as $\Delta int_t Dum_{t,1}$ and $exc_t(1 - Dum_{t,2})$ are non-negative terms. Thus, herding behaviour tend to be strong as the interest rate increases or ZAR depreciation is large. By the same token, if decrease in interest rates and appreciation of ZAR is considered as good news and prompt herding behaviour, then δ_4 and δ_5 will be significantly positive as $\Delta int_t \left(1 - Dum_{t,1}\right)$ and $\Delta exc_t Dum_{t,2}$ are nonpositive values. Subsequently, the effects of changes in interest rates and exchange rates on herding behaviour are tested by terms δ_3 to δ_6.

5.3.2 Markov Regime switching model for herd behaviour

This study follows the approach by Gong and Dai (2017), Fu and Wu (2020) and Mand and Sifat (2021) with some adjustments in specifying the two-state Markov switching model as follows:

$$Dispersion_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}\Delta int_t Dum_{t,1}R_{m,t}^2 + \delta_{4,s_t}\Delta int_t\left(1 - Dum_{t,1}\right)R_{m,t}^2 + \delta_{5,s_t}\Delta exc_t Dum_{t,2}R_{m,t}^2 + \delta_{6,s_t}\Delta exc_t(1 - Dum_{t,2})R_{m,t}^2 + \delta_{7,s_t}DumApp_t R_{m,t}^2 + \delta_{8,s_t}DumDep_t R_{m,t}^2 + \delta_{9,s_t}Dispersion_{t-1} + \sigma_{s_t}\varepsilon_t \quad (5.3)$$

Where: $\varepsilon_t \sim i.i.d.\left(0, \sigma_{S_t}^2\right)$; S_t is a discrete regime indicator taking values in {1,2} and following two-state Markov switching process. The transition probabilities of the Markov chain to fulfil the above specification is defined as follows:

$$p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\} \quad (5.4)$$

Where: p_{xy} expresses the probability of being in regime x occurring at time $t+1$ provided that the market was in regime y at time t. The transition probabilities above satisfy $\sum_{i=0}^{1} p_{xy} = 1$

5.4 Data description

All data relating to weekly and monthly stock prices for empirical analysis in this study are obtained from NSX for the period 1st January 2003 to 30th June 2023 as explained before. Data regarding cross sectional absolute deviation ($Dispersion$), market returns ($R_{m,t}$), and squared of markets returns ($R_{m,t}^2$) for all equity stocks as well as for different sectors are as defined in the previous chapters. Weekly and monthly data relating to exchange and interest rates as proxied by the Johannesburg Interbank Average Rate (JIBAR) 3 month yield rates are obtained from McGregor BFA database.

5.5 Empirical results

5.5.1 The effects of changes in exchange and interest rates on herding behaviour under the static model

Table 5.2 through Table 5.5 presents the results of the static models based on Equation 5.1. The coefficient δ_2 is either positive or negative but insignificant which points to the absence of herding behaviour for the whole market and all sectors for the period under review. The results of the static model indicated that the linear relationship between cross sectional standard deviation and average market returns holds. Thus, under market stress market participants tend to not cluster around the aggregate market returns. Results in Table 5.2 shows that δ_3 and δ_6 are significantly negative for the Whole market and the Resources sector which indicates that interest rate increase and ZAR depreciation amplifies herding behaviour when using equally weighted weekly data. This showed that market participants may be more sensitive to bad news than good news. This finding is consistent with previous studies like Gong and Dai (2017) and Rahman and Wati (2020).

Table 5.2: Regression results for the static model using the OLS for the equally weighted weekly data

	All equity	Financials	Industrials	Resources	Services
α	0.6100**	0.4121**	0.1832**	0.7348**	0.3689**
δ_1	0.4936**	0.6322**	1.1819**	0.2266**	0.6234**
δ_2	0.2817**	0.1391**	0.0048	0.0883**	0.0973**
δ_3	-0.7110**	-0.2782	-0.0913	-0.5676**	-0.2489
δ_4	-0.1211	-0.0826	-0.1178	0.1540	0.1039
δ_5	0.1178**	0.1795**	0.0357	-0.0675	0.0218
δ_6	-0.1728**	-0.0438	-0.0391	-0.0775	-0.0167
δ_7	0.1002	-0.0335	-0.0881	0.1059**	0.0328
δ_8	0.0151	0.2349**	-0.0833	0.0029	-0.0792
δ_9	0.0862**	0.0821**	0.0384**	0.1588**	0.0541**
log L	-409.91	-302.70	-980.78	-1297.8	-1035.3
AIC	839.8	625.4	1982	2616	2091
BIC	889.6	675.2	2031	2665	2140
Adj. R^2	0.671	0.699	0.851	0.435	0.783

Notes: The table presents results for the following static model

$$CSAD_t = \alpha_0 + \delta_1 |R_{m,t}| + \delta_2 R_{m,t}^2 + \delta_3 \Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_4 \Delta int_t (1 - Dum_{t,1}) R_{m,t}^2 + \delta_5 \Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_6 \Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_7 DumApp_t R_{m,t}^2 + \delta_8 DumDep_t R_{m,t}^2 + \delta_9 CSAD_{t-1} + \varepsilon_t.$$

** Indicates significant at the 5% level of significance. Log L , AIC, BIC, Adj. R^2 denotes log likelihood of the OLS method, Akaike Information Criterion, Bayes-Schwartz Information Criterion and adjusted coefficient of determination respectively.

Table 5.3: Regression results for the static model using the OLS for the value weighted weekly data

	All equity	Financials	Industrials	Resources	Services
α	0.0165**	0.0215**	0.0592**	0.0200**	0.1145**
δ_1	1.1343**	1.0408**	1.1127**	1.3163**	0.5012**
δ_2	1.2073**	0.4153**	0.0158	-0.0032	0.3845**
δ_3	-1.1752**	0.1083	-0.2102	-0.1276	-0.5910
δ_4	-1.3945**	-0.6509**	0.0832	-0.2628**	0.4961
δ_5	0.8654**	0.0078	-0.0894	0.0889	0.0766
δ_6	-0.1126	-0.2272	0.2673	-0.1596	-0.4855**
δ_7	-0.2970	0.2082	-0.3519	0.1202	0.2078
δ_8	-0.1903	-0.0136	-0.1629	0.1945**	-0.2164
δ_9	0.0562**	0.0557**	0.0185	0.0208**	0.0438**
$\log L$	3046.3	2811.3	692.81	556.08	687.62
AIC	-6073	-5603	-1366	-1092	-1355
BIC	-6023	-5553	-1316	-1042	-1305
Adj. R^2	0.884	0.917	0.874	0.925	0.813

Notes: The table presents results for the following static model

$$CSADWGHT_t = \alpha_0 + \delta_1 \left|R_{m,t}\right| + \delta_2 R_{m,t}^2 + \delta_3 \Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_4 \Delta int_t \left(1 - Dum_{t,1}\right) R_{m,t}^2 + \delta_5 \Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_6 \Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_7 DumApp_t R_{m,t}^2 + \delta_8 DumDep_t R_{m,t}^2 + \delta_9 CSADWGHT_{t-1} + \varepsilon_t.$$

** Indicates significant at the 5% level of significance. Log L , AIC, BIC, Adj. R^2 denotes log likelihood of the OLS method, Akaike Information Criterion, Bayes-Schwartz Information Criterion and adjusted coefficient of determination respectively.

Table 5.4: Regression results for the static model using the OLS for the equally weighted monthly data

	All equity	Financials	Industrials	Resources	Services
α	1.3150**	1.1421**	0.8048**	2.2265**	1.4179**
δ_1	0.4891**	0.2604	0.6052**	-0.1136	0.0949
δ_2	0.0307	0.0808**	0.0432	0.0892**	0.1185
δ_3	-0.1044	0.1370	-0.0689**	-0.0401	-0.1000
δ_4	-0.0174	-0.0060	-0.0412	0.0192	-0.0364
δ_5	-0.0528	-0.0418	0.0223	-0.0048	0.0994
δ_6	-0.0013	0.1346**	-0.0452	-0.0192	-0.0163
δ_7	0.0071	-0.2742**	0.0017	0.00006664	-0.0056
δ_8	-0.3105**	-0.0385	-0.0851	0.0979	0.0755
δ_9	0.2089**	0.1203**	0.1826**	0.0563	0.1026**
$\log L$	-299.98	0.701	-377.65	-475.61	-438.55
AIC	620.0	-257.08	775.3	971.2	897.1
BIC	655.0	534.2	810.3	1006	932.1
Adj. R^2	0.480	569.2	0.780	0.381	0.696

Notes: The table presents results for the following static model

$$CSAD_t = \alpha_0 + \delta_1 |R_{m,t}| + \delta_2 R_{m,t}^2 + \delta_3 \Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_4 \Delta int_t (1 - Dum_{t,1}) R_{m,t}^2 + \delta_5 \Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_6 \Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_7 DumApp_t R_{m,t}^2 + \delta_8 DumDep_t R_{m,t}^2 + \delta_9 CSAD_{t-1} + \varepsilon_t.$$

** Indicates significant at the 5% level of significance. Log L , AIC, BIC, Adj. R^2 denotes log likelihood of the OLS method, Akaike Information Criterion, Bayes-Schwartz Information Criterion and adjusted coefficient of determination respectively.

Table 5.5: Regression results for the static model using the OLS for the value weighted monthly data

	All equity	Financials	Industrials	Resources	Services
α	0.0573**	0.0556**	0.1824**	0.1497**	0.2881**
δ_1	0.6996**	0.8719**	1.0523**	1.2303**	0.4817**
δ_2	2.2515**	0.2656	0.0759**	0.0015	0.2667**
δ_3	0.4880	-0.0959	-0.0696	-0.0657	-0.3598
δ_4	0.4896	0.1669	-0.3163**	-0.0232	0.0572
δ_5	-0.8717	-0.7950**	0.1653	-0.1296**	0.3545
δ_6	0.6830	0.3898**	-0.2925**	-0.0362	-0.0551
δ_7	-1.6751	-0.3256	0.1480	0.1096	0.1668
δ_8	0.0226	0.1028	-0.4104**	0.1009	0.4684**
δ_9	0.0248	0.0558**	0.0050	-0.0326	0.0183
log L	494.07	497.04	-29.233	-57.199	-48.745
AIC	-968.1	-974.1	78.47	134.4	117.5
BIC	-933.1	-939.1	113.5	169.4	152.5
Adj. R^2	0.780	0.914	0.874	0.900	0.881

Notes: The table presents results for the following static model

$$CSADWGHT_t = \alpha_0 + \delta_1\left|R_{m,t}\right| + \delta_2 R_{m,t}^2 + \delta_3 \Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_4 \Delta int_t\left(1 - Dum_{t,1}\right) R_{m,t}^2 + \delta_5 \Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_6 \Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_7 DumApp_t R_{m,t}^2 + \delta_8 DumDep_t R_{m,t}^2 + \delta_9 CSADWGHT_{t-1} + \varepsilon_t.$$

** Indicates significant at the 5% level of significance. Log L , AIC, BIC, Adj. R^2 denotes log likelihood of the OLS method, Akaike Information Criterion, Bayes-Schwartz Information Criterion and adjusted coefficient of determination respectively.

From Table 5.2 above, δ_5 is significantly positive for the Whole market and financial sector suggesting ZAR appreciation is viewed as good news and induces herding behaviour also consistent with Gong and Dai (2017). Furthermore, δ_7 is significantly positive under the resources sector which also suggest that extreme changes in ZAR appreciation is viewed as good news in this sector and amplifies herding behaviour which when contrasted to the finding by Gong and Dai (2017). δ_8 is significantly positive under the Financials sector suggesting that bad news in the extreme ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector.

Results in Table 5.3 above shows that δ_3 and δ_6 are significantly negative for the whole market and the Services sector, respectively, implying that an increase in interest rate and ZAR depreciation amplifies herding behaviour when using equally weighted weekly data. This also showed that market participants may be more sensitive to bad news than good news. δ_5 is significantly positive for the whole market and financial sector suggesting ZAR appreciation is viewed as good news and induces herding behaviour also consistent with Gong and Dai (2017). δ_4 is significantly negative for the Whole market, Financial and Resource sectors suggesting that interest rate increases is viewed as good news and weakens herding behaviour in these sectors. δ_5 is significantly positive for the Whole market suggesting that ZAR depreciation is viewed as good news and induce herding behaviour. Furthermore, δ_8 is significantly positive under the Resources sector suggesting that bad news in the extreme ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector.

Table 5.4 above shows that δ_3 is significantly negative for the Industrials sector which indicates that an increase in interest rate amplifies herding behaviour when using equally weighted monthly data. This shows that market participants may be more sensitive to bad news than good news. This finding is also consistent with previous studies which include Gong and Dai (2017) and Rahman and Wati (2020). However, δ_6 is significantly positive for the Financials sectors suggesting that bad news in the ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector. δ_7 is significantly negative under the financial sector which also suggest that extreme changes in ZAR appreciation is viewed as good news and intensifies the market participants' divergence and reduces herding behaviour in this sector. δ_8 is significantly negative for the whole market suggesting that extreme ZAR depreciation is viewed as bad news and amplifies herding behaviour in the emerging markets corroborating the findings by Gong and Dai (2017).

Results in Table 5.5 above shows that δ_6 is significantly negative for the Industrials sector implying that ZAR depreciation amplifies herding behaviour when using equally weighted monthly data. This also shows that market participants may be more sensitive to bad news than good news. However, δ_6 is significantly positive for the financials sectors suggesting that bad news in the ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector. δ_4 and δ_5 is are significantly negative for the Industrial, Financial and Resource sectors suggesting that interest rate increases and ZAR appreciation are viewed as good news and weakens herding behaviour in these sectors. Furthermore, δ_8 is significantly positive under the

Services sector suggesting that bad news in the extreme ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector. However, δ_8 is significantly negative for the Industrials sector suggesting that extreme ZAR depreciation is viewed as bad news and amplifies herding behaviour in the emerging markets corroborating the findings by Gong and Dai (2017).

5.5.2 The effects of changes in exchange and interest rates on herd behaviour under different regimes

Table 5.6 through Table 5.9 below presents the empirical results of the two-state Markov switching herding model. The Markov Switching Regime models have higher log likelihood and lower information criteria values compared to those of the static models in Table 5.2 through 5.5. This shows the regime switching model is statistically superior to the static model. The finding also validates the preference of the regime switching model to the static model in this study. Empirical results in Table 5.6 reveals that the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for all equity market and the sectors. In this regard, $\hat{\sigma}_2$ corresponded to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime for the equally weighted weekly data. The regime transition probabilities are all statistically significant for all equity stocks and the sectors which also indicated stability of the hidden market regimes inferred from the models and tend to remain in the current regimes.

Table 5.6: Regime switching model results using equally weighted weekly data.

Parameter	All equity	Financials	Industrials	Resources	Services
α_1	0.5352** (26.094)	0.3877** (21.435)	0.3032** (16.881)	0.6416** (17.005)	0.3520** (15.114)
α_2	1.0855** (11.079)	0.7096** (10.930)	0.5601** (5.869)	0.9726** (7.572)	0.9969** (11.311)
δ_{11}	0.4159** (11.300)	0.5274** (12.653)	0.6387** (19.036)	-0.0076 (-0.163)	0.3686** (14.723)
δ_{12}	0.4140** (2.017)	0.7159** (6.666)	1.4653** (20.454)	0.2922** (3.273)	0.5033** (5.112)
δ_{21}	0.2438** (13.401)	0.0801** (3.005)	0.0919** (6.878)	0.0981** (7.893)	0.1036** (20.279)
δ_{22}	0.7670** (7.565)	0.1132** (3.188)	-0.0319** (-2.986)	0.0461** (2.613)	0.1826** (9.937)
δ_{31}	-0.8411** (-5.084)	0.3828** (3.639)	0.0416 (0.447)	-0.3101** (-4.194)	0.1283 (1.010)
δ_{32}	-1.5631** (-6.639)	-0.5043 (-0.936)	-0.3009** (-4.387)	-0.4924** (-4.845)	-0.4945** (-4.577)
δ_{41}	-0.1983** (-4.574)	-0.3212** (-5.058)	0.1022** (2.068)	0.1480** (2.696)	-0.0368 (-1.203)
δ_{42}	0.4851** (2.356)	-0.1259 (-1.787)	-0.0527 (-0.981)	0.2611** (2.400)	-0.3046 (-1.464)
δ_{51}	0.0629 (1.817)	0.1128 (1.467)	0.1303** (4.178)	-0.0321 (-0.930)	0.0943** (2.246)
δ_{52}	0.4178 (1.636)	0.0986 (0.861)	-0.1969** (-2.723)	-0.4550** (-5.782)	0.1200 (1.528)
δ_{61}	-0.1946** (-4.393)	-0.0476 (-0.917)	-0.2176** (-4.468)	0.1449** (2.486)	-0.1634** (-5.813)
δ_{62}	-0.8941** (-4.420)	0.3558** (2.661)	-0.0520 (-0.895)	-0.0446 (-1.652)	-0.1304 (-1.770)

δ_{71}	0.1880** (3.128)	0.5379** (6.502)	0.1736** (2.837)	0.3497** (3.867)	-0.0433 (-0.593)
δ_{72}	0.6691** (2.679)	-0.5999** (-3.295)	-0.1143 (-0.911)	0.0777** (2.815)	0.2457 (1.149)
δ_{81}	0.0050 (0.130)	0.1817 (1.637)	0.1333** (3.096)	0.5322** (4.399)	-0.0266 (-0.949)
δ_{82}	0.2204 (0.706)	0.2067** (2.367)	-0.2881** (-4.822)	-0.4459** (-4.787)	-0.0025 (-0.022)
δ_{91}	0.1088** (6.362)	0.0380** (2.464)	0.0043 (0.574)	0.0671** (3.797)	0.0385** (2.794)
δ_{92}	-0.0646 (-1.557)	-0.0118 (-0.307)	-0.0072 (-0.276)	0.2944** (3.810)	-0.0731** (-2.888)
σ_1	0.0420**	0.0295**	0.0629**	0.1344**	0.0575**
σ_2	0.1669**	0.1547**	0.6423**	0.7342**	0.5542**
p_{11}	0.8317**	0.9050**	0.8649**	0.6007**	0.7412**
p_{22}	0.6664**	0.2291**	0.3901**	0.5233**	0.6018**
τ_1	5.94	10.52	7.40	2.50	3.86
τ_2	1.50	4.36	2.56	1.91	1.66
n	1077	1077	1077	1077	1077
$\log L$	-195.547	-74.658	-610.544	-1127.929	-656.992
AIC	439.094	197.316	1269.088	2303.859	1361.984
BIC	558.660	316.882	1388.655	2423.425	1481.551
HQIC	484.373	242.595	1314.368	2349.138	1407.264

Notes: This table presents results of the following two regime Markov switching model:
$CSAD_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}\Delta int_t Dum_{t,1}R_{m,t}^2 + \delta_{4,s_t}\Delta int_t\left(1 - Dum_{t,1}\right)R_{m,t}^2 + \delta_{5,s_t}\Delta exc_t Dum_{t,2}R_{m,t}^2 + \delta_{6,s_t}\Delta exc_t(1 - Dum_{t,2})R_{m,t}^2 + \delta_{7,s_t}DumApp_t R_{m,t}^2 + \delta_{8,s_t}DumDep_t R_{m,t}^2 + \delta_{9,s_t}CSAD_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$
$\log L$, AIC, BIC, HQIC denotes log likelihood, Akaike Information Criterion, Bayes-Schwartz Information Criterion, denotes Hannan-Quinn Information Criterion respectively; τ_k denotes the duration of regime k.
** Indicates statistically significant at 5% level. The numbers in parenthesis are the values of the statistical z-ratios.

Table 5.7: Regime switching model results using value weighted weekly data.

Parameter	All equity	Financials	Industrials	Resources	Services
α_1	0.0274** (5.646)	0.0188** (19.584)	0.0298** (5.466)	0.1743** (3.369)	0.0719** (16.960)
α_2	0.0155** (22.011)	0.0342** (6.634)	0.1309** (4.827)	0.0061 (1.525)	0.1793** (12.953)
δ_{11}	1.3233** (7.098)	1.0153** (48.977)	1.3541** (34.790)	0.6475** (5.829)	0.5260** (23.184)
δ_{12}	1.1120** (46.914)	1.0306** (11.292)	1.0211** (11.431)	1.3918** (98.214)	0.5773** (13.064)
δ_{21}	-1.7321 (-0.796)	0.7087** (5.990)	-0.1925** (-5.294)	0.2457** (4.912)	0.0759** (2.772)
δ_{22}	1.2771** (6.536)	-1.1166 (-1.585)	0.0675 (0.965)	-0.0283** (-2.155)	0.3836** (8.358)
δ_{31}	45.8719** (2.811)	-0.0506 (-0.134)	-0.3868 (-1.590)	-0.2698 (-1.193)	-0.3481** (-2.913)
δ_{32}	-1.2475 (-1.358)	1.9214 (0.769)	-0.3493** (-2.476)	-0.1490** (-2.636)	-1.2232** (-2.825)
δ_{41}	-1.4528 (-0.633)	-0.0901 (-0.436)	-0.6037** (-2.860)	-1.1349** (-3.890)	-0.0561 (-0.617)
δ_{42}	-2.7656** (-6.187)	-3.2589 (-1.185)	0.2320 (1.103)	0.0511 (1.939)	-0.1904 (-0.458)
δ_{51}	-0.9651 (-0.270)	0.1818 (1.079)	1.0953** (11.070)	0.1389 (1.550)	0.0488 (0.725)
δ_{52}	0.4233 (1.214)	-4.9677 (-1.922)	-0.1440** (-2.061)	-0.1534** (-5.535)	0.0170 (0.090)
δ_{61}	2.1659 (0.491)	-0.5632** (-2.165)	-0.8162** (-7.728)	-0.2956** (-3.983)	0.0278 (0.406)
δ_{62}	-0.4288 (-0.925)	5.1177** (2.332)	0.3867** (2.794)	0.1219** (4.817)	-0.6769** (-3.718)

δ_{71}	-6.4018 (-1.318)	1.1434** (3.399)	1.1404** (8.931)	-0.0929 (-0.584)	0.0087 (0.127)
δ_{72}	-0.0581 (-0.094)	-6.1194** (-2.266)	-0.5172** (-3.132)	-0.0706** (-2.040)	3.9891** (3.223)
δ_{81}	-1.9109 (-0.403)	0.0775 (0.566)	-0.2168 (-0.689)	0.4503** (3.077)	0.0406 (0.450)
δ_{82}	-0.5181 (-1.175)	-7.0558** (-2.347)	-0.2537** (-2.777)	-0.1809** (-3.451)	-0.4931** (-3.544)
δ_{91}	0.1853** (3.394)	0.0362** (5.381)	-0.0097 (-1.045)	0.0695** (2.182)	-0.0156 (-1.142)
δ_{92}	0.0240** (2.899)	0.2131** (4.907)	0.0272 (0.779)	0.0031 (0.778)	0.0285 (1.741)
σ_1	0.0005**	0.0001**	0.0037**	0.0728**	0.0015**
σ_2	0.00007**	0.0005**	0.0397**	0.0028**	0.0176**
p_{11}	0.1407**	0.8324**	0.8552**	0.9356**	0.6338**
p_{22}	0.1291**	0.8310**	0.4058**	0.0119**	0.4102**
τ_1	1.16	5.96	6.90	74.12	2.73
τ_2	7.74	1.20	2.46	13.06	2.43
n	1077	1077	1077	1077	1077
log L	3288.500	2983.491	949.543	1293.923	974.331
AIC	-6529.000	-5918.983	-1851.085	-2539.846	-1900.662
BIC	-6409.434	-5799.417	-1731.519	-2420.279	-1781.096
HQIC	-6483.721	-5873.703	-1805.806	-2494.566	-1855.383

Notes: This table presents results of the following two regime Markov switching model:
$CSADWGHT_t = \alpha_{0,s_t} + \delta_{1,s_t}\left|R_{m,t}\right| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}\Delta int_t Dum_{t,1}R_{m,t}^2 + \delta_{4,s_t}\Delta int_t\left(1 - Dum_{t,1}\right)R_{m,t}^2 + \delta_{5,s_t}\Delta exc_t Dum_{t,2}R_{m,t}^2 + \delta_{6,s_t}\Delta exc_t(1 - Dum_{t,2})R_{m,t}^2 + \delta_{7,s_t}DumApp_t R_{m,t}^2 + \delta_{8,s_t}DumDep_t R_{m,t}^2 + \delta_{9,s_t}CSADWGHT_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$
log L , AIC, BIC, HQIC denotes log likelihood, Akaike Information Criterion, Bayes-Schwartz Information Criterion, denotes Hannan-Quinn Information Criterion respectively; τ_k denotes the duration of regime k.
** Indicates statistically significant at 5% level. The numbers in parenthesis are the values of the statistical z-ratios.

Table 5.8: Regime switching model results using equally weighted monthly data.

Parameter	All equity	Financials	Industrials	Resources	Services
α_1	1.4407** (13.541)	1.4555** (5.308)	0.9471** (7.647)	1.0908** (11.444)	1.2585** (8.795)
α_2	0.5307 (1.456)	1.0160** (15.374)	1.0249** (3.423)	2.4336** (8.246)	0.5022 (1.669)
δ_{11}	0.5588** (4.567)	0.6136** (2.946)	0.6929** (8.023)	0.2177** (4.635)	0.1772 (1.941)
δ_{12}	2.3334** (6.648)	0.2452** (3.317)	1.0656** (4.235)	-0.1441 (-0.978)	0.1358** (6.309)
δ_{21}	-0.1056** (-2.265)	0.0047 (0.111)	-0.1594** (-4.897)	-0.1913** (-29.016)	0.0038 (0.239)
δ_{22}	0.1186 (1.058)	0.0683** (5.347)	-0.0161 (-0.414)	0.0937** (5.004)	-0.1806 (-1.497)
δ_{31}	-0.1308 (-1.372)	-0.1764 (-1.317)	0.0593** (2.879)	0.0624** (4.040)	0.0262 (0.585)
δ_{32}	4.7148** (6.162)	0.0649 (1.166)	-0.1264 (-1.188)	-0.0317 (-0.658)	-0.0966 (-1.402)
δ_{41}	-0.1222** (-4.589)	-0.0259 (-1.111)	-0.1744** (-9.541)	0.2053** (24.727)	0.0996 (1.736)
δ_{42}	-0.7610** (-3.475)	-0.2067** (-8.456)	-0.0965 (-1.884)	0.0174 (1.194)	0.4132** (5.241)
δ_{51}	-0.2192** (-4.583)	-0.0438 (-0.602)	-0.2086** (-5.249)	-0.4934** (-49.309)	-0.2993** (-10.174)
δ_{52}	2.0817** (6.206)	0.0805 (1.567)	0.1067** (2.413)	0.0009 (0.026)	-0.1304 (-1.283)
δ_{61}	0.1053** (2.543)	-0.0639 (-1.381)	0.2245** (5.586)	0.2885** (51.383)	0.0406 (1.561)
δ_{62}	-1.2886** (-7.450)	0.2580** (15.976)	-0.1233** (-2.908)	-0.0262 (-1.123)	0.1099 (0.645)

δ_{71}	0.0539 (0.901)	0.1625 (1.647)	-0.3134** (-4.749)	-0.0816 (-1.573)	-0.0224 (-0.188)
δ_{72}	1.8207** (5.204)	-0.1953** (-3.070)	0.0948 (0.975)	0.0058 (0.172)	0.1505 (0.283)
δ_{81}	-0.3358 (-1.172)	-0.2766 (-0.382)	-0.1562 (-1.246)	0.6648 ** (14.689)	-0.2572** (-2.828)
δ_{82}	-0.1147 (-0.083)	0.0857 (0.320)	-0.4503 (-0.281)	-0.2068 (-0.466)	0.0345 (0.398)
δ_{91}	0.1081** (3.309)	0.1148 (1.439)	-0.0738 (-1.839)	0.0552** (3.395)	0.0629** (0.019)
δ_{92}	0.7223** (6.580)	0.0437** (2.257)	0.1797** (4.124)	0.0470 (0.862)	2.2403** (4.372)
σ_1	0.2537**	0.5387**	0.2286**	0.0106**	0.4805**
σ_2	0.1397	0.0656**	1.5954**	2.9319**	2.1975**
p_{11}	0.9246**	0.7065**	0.8554**	0.1029**	0.7949**
p_{22}	0.8694**	0.2087**	0.1730**	0.1472**	0.6837**
τ_1	13.2	3.40	6.91	1.11	4.87
τ_2	1.15	4.79	5.78	6.79	1.46
n	246	246	246	246	246
$\log L$	-227.138	-187.279	-328.408	-452.016	-351.111
AIC	502.275	422.557	704.816	952.033	750.222
BIC	586.403	506.685	788.944	1036.161	834.350
HQIC	536.150	456.432	738.690	985.907	784.096

Notes: This table presents results of the following two regime Markov switching model:
$CSAD_t = \alpha_{0,s_t} + \delta_{1,s_t}|R_{m,t}| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}\Delta int_t Dum_{t,1}R_{m,t}^2 + \delta_{4,s_t}\Delta int_t\left(1 - Dum_{t,1}\right)R_{m,t}^2 + \delta_{5,s_t}\Delta exc_t Dum_{t,2}R_{m,t}^2 + \delta_{6,s_t}\Delta exc_t(1 - Dum_{t,2})R_{m,t}^2 + \delta_{7,s_t}DumApp_t R_{m,t}^2 + \delta_{8,s_t}DumDep_t R_{m,t}^2 + \delta_{9,s_t}CSAD_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$
$\log L$, AIC, BIC, HQIC denotes log likelihood, Akaike Information Criterion, Bayes-Schwartz Information Criterion, denotes Hannan-Quinn Information Criterion respectively; τ_{k} denotes the duration of regime k.
** Indicates statistically significant at 5% level. The numbers in parenthesis are the values of the statistical z-ratios.

Table 5.9: Regime switching model results using value weighted monthly data.

Parameter	All equity	Financials	Industrials	Resources	Services
α_1	0.0451** (11.600)	0.0557** (14.078)	0.1720** (3.768)	-0.0101 (-0.521)	0.1163** (6.241)
α_2	0.1390** (4.927)	0.1441** (15.102)	0.0633** (2.063)	0.2414** (2.622)	0.3508** (6.296)
δ_{11}	0.7109** (9.689)	0.8642** (18.146)	1.0281** (13.753)	1.6020** (19.465)	0.6954** (9.993)
δ_{12}	-0.5173 (-0.758)	0.7058** (4.482)	1.6839** (15.322)	1.1963** (11.316)	0.4944** (5.452)
δ_{21}	2.2714** (4.986)	0.3243** (2.057)	0.0568** (2.530)	-0.2918** (-3.730)	-0.3257** (-4.639)
δ_{22}	11.6282** (2.129)	-1.5310** (-2.194)	-1.3752** (-12.030)	0.0012 (0.045)	0.2649** (11.729)
δ_{31}	0.8861 (0.657)	-0.0271 (-0.089)	-0.1372 (-1.336)	0.3010** (5.004)	-0.2174 (-0.535)
δ_{32}	11.3632 (0.773)	0.4852 (0.773)	1.4599** (11.145)	-0.2284** (-1.977)	-0.4927** (-2.546)
δ_{41}	0.4154 (1.484)	0.1195 (1.013)	0.0178 (0.175)	-0.1326** (-5.425)	-0.1378** (-3.072)
δ_{42}	5.7610** (2.189)	-0.3616 (-1.167)	0.2055 (1.511)	-0.0103 (-0.247)	0.1742 (1.004)
δ_{51}	0.0125 (0.025)	-0.7767** (-3.414)	0.0602 (0.840)	0.1488** (2.371)	-0.5533** (-6.080)
δ_{52}	-11.3820** (-2.694)	-4.4137** (-5.210)	-0.8193** (-8.178)	-0.1612** (-2.740)	0.3011 (1.496)
δ_{61}	1.1512** (2.520)	0.3329** (2.513)	0.0635 (0.775)	-0.2289** (-4.748)	0.4777** (4.308)
δ_{62}	-8.1366 (-1.714)	9.5477** (10.142)	1.1550** (10.285)	0.0057 (0.146)	-0.0594 (-0.627)

δ_{71}	-2.6964** (-3.164)	-0.2737 (-1.223)	-0.3633** (-3.094)	0.3069** (5.954)	-0.4242** (-4.272)
δ_{72}	0.6641 (0.070)	-13.4989** (-9.889)	-0.9229** (-6.381)	0.0381 (0.326)	0.9801** (2.261)
δ_{81}	2.4712 (1.315)	0.2395 (0.421)	-0.6934 (-0.875)	0.3951** (4.838)	2.3026** (4.411)
δ_{82}	-18.4869 (-1.221)	-3.8960** (-3.406)	-1.6262** (-4.675)	22.6511** (4.139)	0.3455 (1.200)
δ_{91}	0.0520** (2.235)	0.0212 (1.442)	0.1112** (2.641)	-0.0145 (-1.218)	-0.0035 (-0.688)
δ_{92}	-0.1494 (-1.477)	0.0707** (2.745)	-0.0260** (-2.197)	-0.0410 (-1.370)	0.0428 (1.013)
σ_1	0.0003**	0.0005**	0.0568**	0.0026**	0.0028**
σ_2	0.0016**	0.0001**	0.0114**	0.1217**	0.0936**
p_{11}	0.8449**	0.9426**	0.5048**	0.5231**	0.5948**
p_{22}	0.7223**	0.8874**	0.7838**	0.3524**	0.1886**
τ_1	6.44	17.42	2.01	2.09	2.46
τ_2	1.38	1.12	1.27	2.83	5.30
n	246	246	246	246	246
log L	555.964	539.527	23.997	20.271	-1.427
AIC	-1063.928	-1031.055	0.006	7.457	50.855
BIC	-979.800	-946.927	84.134	91.585	134.983
HQIC	-1030.053	-997.181	33.880	41.332	84.729

Notes: This table presents results of the following two regime Markov switching model:
$CSADWGHT_t = \alpha_{0,s_t} + \delta_{1,s_t}|R_{m,t}| + \delta_{2,s_t}R_{m,t}^2 + \delta_{3,s_t}\Delta int_t Dum_{t,1} R_{m,t}^2 + \delta_{4,s_t}\Delta int_t (1 - Dum_{t,1}) R_{m,t}^2 + \delta_{5,s_t}\Delta exc_t Dum_{t,2} R_{m,t}^2 + \delta_{6,s_t}\Delta exc_t (1 - Dum_{t,2}) R_{m,t}^2 + \delta_{7,s_t} DumApp_t R_{m,t}^2 + \delta_{8,s_t} DumDep_t R_{m,t}^2 + \delta_{9,s_t} CSADWGHT_{t-1} + \sigma_{s_t}\varepsilon_t$, where $p_{xy} = P(s_{t+1} = x|s_t = y), x, y \in \{1,2\}$
log L , AIC, BIC, HQIC denotes log likelihood, Akaike Information Criterion, Bayes-Schwartz Information Criterion, denotes Hannan-Quinn Information Criterion respectively; τ_k denotes the duration of regime k.
** Indicates statistically significant at 5% level. The numbers in parenthesis are the values of the statistical z-ratio

As mentioned in the previous chapter, the transition probability of switching from high volatility regime to a low volatility is estimated by $1 - \hat{p}_{22}$, whereas the transition probability of switching from low volatility regime to a high volatility regime is estimated by $1 - \hat{p}_{11}$. Thus, from Table 5.6 above, the transition probabilities of moving from high volatility regimes to low volatility regimes are: 0.3336, 0.7709, 0.6099, 0.4767 and 0.3982 for All equity stocks, financial, industrial, resource and service sectors respectively. The transition probabilities of moving from low volatility regimes to high volatility regimes are thus: 0.1683, 0.095, 0.1351, 0.3993 and 0.2588 for All equity stocks, financial, industrial, resource and service sectors respectively. Apart from volatility clustering, the results of the transition probabilities indicated that the low volatility regimes are more stable and less persistent than the high volatility regimes. Furthermore, the diagonal elements of the transition probability matrices for all equity stocks and the sectors are much larger than their non-diagonal counterparts which may point to the fact that the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 5.6, on a sectoral level, novel evidence of herding behaviour is exhibited under the industrials sector for the high volatility regime as evidenced by statistically significant negative δ_{21}. These findings are also consistent with previous studies like Babalos *et al.* (2015) and Mand and Sifat (2021). However, these findings are in contrast to that of the static models which found absence of herding behaviour. The results in Table 5.6 also shows that δ_3 is significantly negative for the whole market and the all the sectors save for the financials sector which indicates that increases in interest rate induces herding behaviour for both low and high volatility regimes. However, δ_{31} is statistically positive suggesting that bad news in interest rate increase intensifies the market participants' divergence and weakens herding behaviour under the financial sector (low volatility regime).

δ_4 is significantly negative under the whole market (low volatility regime) and the financial sector (low volatility regime). This suggest that good news in interest rate decrease intensifies the market participants' divergence and weakens herding behaviour. δ_4 is significantly positive for the whole market (high volatility regime), Resources sector (both low and high volatility regimes) and industrials sector (low volatility regime). This shows interest rate decrease is viewed as good news by market participants in these sectors and induce herding behaviour. This supports the notion that market participants prefer to invest in stocks than in the banks when interest rates are very low.

δ_5 is significantly negative for Industrials sector (high volatility regime) and Resources sector (high volatility regime). The results show that good news in ZAR appreciation intensifies the market participants' divergence and weakens herding behaviour in these sectors. However, δ_5 is significantly positive for industrials sector (low volatility regime) and Services sector (low volatility regime). This indicates that good news in ZAR appreciation induce herding behaviour in these sectors. δ_6 is significantly negative under the whole market (both low and high volatility regimes), the Industrials sector (low volatility regime) as well as the Services sector (low volatility regime). This suggest ZAR depreciation is viewed as bad news by the investors and induce herding behaviour in the whole market and these sectors. However, δ_6 is significantly positive for financials sector (high volatility regime) and Resources sector (low volatility regime). This indicated that bad news in ZAR depreciation intensifies the market participants' divergence and weakens herding behaviour in these sectors.

δ_7 is significantly positive for the whole market (low and high volatility regimes), financials sector (low volatility regime), Industrials sector (low volatility regime) and Resources sector (both low and high volatility regimes). This indicated that the extreme changes in ZAR appreciation is seen as good news by the investors and induce herding behaviour. δ_7 is significantly negative for the financials sector (high volatility regime). This indicates that good news in extreme changes in ZAR appreciation intensifies the market participants' divergence and weakens herding behaviour in this sector. δ_8 is significantly positive for the financials sector (low volatility regime) and industrials sector (low volatility regime) and resources sector (low volatility regime). This indicated that bad news in the extreme changes in ZAR depreciation intensifies the market participants' divergence and weakens herding behaviour in these sectors. δ_8 is significantly negative for the Industrials sector (high volatility regime) and Resources sector (high volatility regime) which indicated that bad news in extreme changes in ZAR depreciation amplified herding behaviour in these sectors consistent with findings by Gong and Dai (2017).

Table 5.6 also provides expected durations of the market regimes. The low volatility regimes tend to be the most persistent as indicated by the longest average regime duration. The average regime duration for the low volatility state ranges from 2.50 for the resources sector to 10.52 weeks for the financials sector. High volatility regimes are more persistent in the financials sector and Industrials sector similar to the findings by Balcilar and Demirer (2015). This also underscores the significance of having hedging instruments to cushion volatility in these sectors. The average shortest regime durations for both low and high volatility regimes is observed under the resource and financial sectors, respectively, thereby implying more frequent regime switching in these sectors. This also shows these two sectors are more volatile as compared to others.

From Table 5.7 above, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for the financial, industrial and service sectors. In this regard, $\hat{\sigma}_2$ corresponds to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime for the value weighted weekly data. The regime transition probabilities are all statistically significant for all equity stocks and the sectors which also indicated stability of the hidden market regimes inferred from the models and tend to remain in the present regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes are: 0.169, 0.5942 and 0.5898 for the financial, industrial and service sectors respectively. The transition probabilities of moving from low volatility regimes to high volatility regimes for these sectors are thus: 0.1683, 0.1448 and 0.3662 respectively. However, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 under the whole market and resources sector are smaller than $\hat{\sigma}_1 s$. In this regard, $\hat{\sigma}_2$ corresponds to the low volatility regime while $\hat{\sigma}_1$ corresponds to the high volatility regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes for the whole market and resources sector are thus: 0.8593 and 0.0119 respectively whilst that of moving from low volatility regimes to high volatility regimes are 0.8709 and 0.9881 respectively.

Apart from volatility clustering, the results of the transition probabilities indicated that the low volatility regimes are more stable and less persistent than the high volatility regimes for the financial, industrial and service sectors as compared to the whole market and resources sector. Furthermore, the diagonal elements of the transition probability matrices for all equity stocks and the sectors are much larger than their non-diagonal counterparts which may point to the fact that the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 5.7, on a sectoral level, novel evidence of herding behaviour is exhibited under the industrials sector (low volatility regime) and the resources sector (low volatility regime) as evidenced by statistically significant negative δ_{21} and δ_{22} ,respectively, which also corroborates with previous studies like Babalos *et al.* (2015) and Mand and Sifat (2021). The results in Table 5.7 also shows that δ_3 is significantly negative for the services sector (both low and high volatility regime), Industrial sectors (high volatility regime) and resources sector (low volatility regime) which indicates that increases in interest rate induces herding behaviour for both low and high volatility regimes. However, bad news in interest rate increase intensifies the market participants' divergence and reduces herding behaviour for the Whole market (high volatility regime) as indicated by a statistically significant positive δ_{31}. δ_4 is significantly negative under the whole market (high volatility regime), industrials sector (low volatility regime) and resources (high volatility regime). This suggest that good news in interest rate decrease intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_5 is significantly negative for industrials sector (high volatility regime) and Resources sector (low volatility regime). The results show that good news in ZAR appreciation intensifies the market participants' divergence and weakens herding behaviour in these sectors. However, δ_5 is significantly positive for industrials sector (low volatility regime). This indicates that good news in ZAR appreciation induce herding behaviour in this sector. δ_6 is significantly negative under the financials sector (low volatility regime), Industrials sector (low volatility regime), Resources sector (high volatility regime) as well as the Services sector (high volatility regime). This suggest bad news in ZAR depreciation induce herding behaviour in these sectors. However, δ_6 is significantly positive for the financials sector (high volatility regime), industrials sector (high volatility regime) and resources sector (low volatility regime). This indicates bad news in ZAR depreciation is intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_7 is significantly positive for the financials sector (low volatility regime), industrials sector (low volatility regime) and services sector (high volatility regime). This indicated that the extreme changes in ZAR appreciation is seen as good news by the investors and induce herding behaviour. However, δ_7 is significantly negative for the financial and industrial sectors under the high volatility regimes and resource sectors under low volatility regimes. This indicated that good news in the extreme changes in ZAR appreciation intensifies the market participants' divergence and reduces herding behaviour in these sector. δ_8 is significantly positive, for the resources sector (high volatility regime). This indicates that bad news in the extreme changes in ZAR depreciation intensifies the market participants' divergence and reduced herding behaviour in this sector. δ_{82} is significantly negative for the financials sector (high volatility regime), Industrials sector (high volatility regime), Resources sector (low volatility regime) and services sector (high volatility regime) which indicated that the extreme changes in ZAR depreciation is seen as bad news by the investors and induce herding behaviour in these sectors consistent with Gong and Dai (2017).

Table 5.7 also provides expected durations of the market regimes. The high volatility regimes tend to be the most persistent as indicated by the longest average regime duration. The average regime duration for the high volatility state ranges from 1.16 for the whole sector to 74.12 weeks for the resources sector. Low volatility regimes are more persistent in the whole market and resources sector. This also underscores the significance of having hedging instruments to cushion volatility in these areas. The average shortest regime durations for both low and high volatility regimes is observed under the service and whole market, respectively, thereby implying more frequent regime switching in these markets. This also shows that these two markets are more volatile as compared to others.

From Table 5.8, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for the Industrial, Resource and Service sectors. In this regard, $\hat{\sigma}_2$ corresponds to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime for the equally weighted monthly data. The regime transition probabilities are all statistically significant for all equity stocks and the sectors which also indicated stability of the hidden market regimes inferred from the models and tend to remain in the present regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes are: 0.827, 0.8528 and 0.3163 for the industrial, resources and service sectors respectively. The transition probabilities of moving from low volatility regimes to high volatility regimes for these sectors are thus: 0.1446, 0.8971 and 0.2051 respectively. However, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 under the whole market and financials sector are smaller than $\hat{\sigma}_1 s$. In this regard, $\hat{\sigma}_2$ corresponds to the low volatility regime while $\hat{\sigma}_1$ corresponds to the high volatility regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes for the whole market and financials sector are thus: 0.0754 and 0.2935 respectively, whilst that of moving from low volatility regimes to high volatility regimes are 0.1306 and 0.7913 respectively.

Apart from volatility clustering, the results of the transition probabilities also indicates that the high volatility regimes are more stable and less persistent than the low volatility regimes for the whole market, financial and resource sectors as compared to the industrial and service sectors. Furthermore, the diagonal elements of the transition probability matrices for all equity stocks and the sectors are much larger than their non-diagonal counterparts which may point to the fact that the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 5.8, novel evidence of herding behaviour is exhibited under high volatility regime for the whole market, industrials sector (low volatility regime) and resources sector (low volatility regime) as evidenced by statistically significant negative δ_{21} which also corroborated with previous studies like Babalos *et al.* (2015) and Mand and Sifat (2021). The results in Table 5.8 also shows that δ_3 is significantly positive for the whole market (low volatility regime), industrials sector (low volatility regime) and resources (low volatility regime) which indicates that bad news in interest rate increase intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_4 is significantly negative under the Whole market (both low and high volatility regimes), financials sector (low volatility regime) and industrials sector (low volatility regime). This shows that good news in interest rate decrease intensifies the market participants' divergence and reduces herding behaviour in these sectors. δ_4 is significantly positive for the resources sector (low volatility regime) and Services sector (high volatility regime). This shows interest rate decrease is viewed as good news by market participants in these sectors and induce herding behaviour and also supported the notion that market participants prefer to invest in stocks than in the banks when interest rates are very low.

δ_5 is significantly negative for the whole market (high volatility regime), industrial, resource and service sectors under the low volatility regimes. The results show that good news in ZAR appreciation intensifies the market participants' divergence and reduces herding behaviour in these sectors. However, δ_5 is also significantly positive for the whole market (low volatility regime) and industrials sector under the high volatility regime which indicates ZAR appreciation is viewed as good news by the investors and induce herding behaviour in these sectors. δ_6 is significantly negative for the whole market (low volatility regime) and financials sector under the high volatility regimes. This suggest that ZAR depreciation is viewed as bad news by the investors and induce herding behaviour in the whole market and this sector. However, δ_6 is significantly positive for the whole market (high volatility regime), financials sector (low volatility regime), Industrials sector (low volatility regime) and resources sector (low volatility regime). This indicates that bad news in ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_7 is significantly positive for the whole market under the low volatility regime which indicated that the extreme changes in ZAR appreciation is seen as good news by the investors and induce herding behaviour. However, δ_7 is also significantly negative for the Financials sector (low volatility regime) and Industrials sector (low volatility regime). This indicates that good news in the extreme changes in ZAR appreciation intensifies the market participants' divergence and reduces herding behaviour in these sector. δ_8 is significantly positive for the resources sector (low volatility regime). This indicated that bad news in the extreme changes in ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour this sector. δ_{81} is significantly negative for the services sector which indicated that the extreme changes in ZAR depreciation is seen as bad news by the investors and induce herding behaviour in this sector during low volatility regime.

Table 5.8 also provides expected durations of the market regimes. The high volatility regimes tended to be the most persistent as indicated by the longest average regime duration. The average regime duration for the high volatility state ranges from 1.46 months for the Services sector to 13.2 for the whole market. Low volatility regimes are more persistent in the industrial and service sectors. This also underscores the significance of having hedging instruments to cushion volatility in these sectors. The average shortest regime durations for both low and high volatility regimes is observed under the resource and service sectors, respectively, thereby implying more frequent regime switching in these sectors. This also shows that these two sectors are more volatile as compared to others.

From Table 5.9, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 are greater than $\hat{\sigma}_1 s$ for Regime 1 for the whole market, resources and service sectors. In this regard, $\hat{\sigma}_2$ corresponds to the high volatility regime while $\hat{\sigma}_1$ corresponds to the low volatility regime for the value weighted monthly data. The regime transition probabilities are all statistically significant for all equity stocks and the sectors which also indicated stability of the hidden market regimes inferred from the models and tend to remain in the present regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes are: 0.2777, 0.6476 and 0.8114 for the whole market, resources and service sectors respectively. The transition probabilities of moving from low volatility regimes to high volatility regimes for these sectors are thus: 0.1551, 0.4769 and 0.4052 respectively. However, the volatility estimators $\hat{\sigma}_2 s$ for Regime 2 under the financial and industrial sectors are smaller than $\hat{\sigma}_1 s$. In this regard, $\hat{\sigma}_2$ corresponds to the low volatility regime while $\hat{\sigma}_1$ corresponds to the high volatility regimes. The transition probabilities of moving from high volatility regimes to low volatility regimes for the financial and industrial sectors are thus: 0.0574 and 0.4952 respectively, whilst that of moving from low volatility regimes to high volatility regimes are 0.1126 and 0.2162 respectively.

Apart from volatility clustering, the results of the transition probabilities also indicated that the high volatility regimes are more stable and less persistent than the low volatility regimes for the whole market, industrial, resource and service sectors as compared to the financial sector. Furthermore, the diagonal elements of the transition probability matrices for all equity stocks and the sectors are much larger than their non-diagonal counterparts which may point to the fact that the regimes from the models are relatively persistent as the current states tend to stay in the previous states.

From Table 5.9, novel evidence of herding behaviour is exhibited for financial, industrial and resource sectors under the low volatility regimes as evidenced by statistically significant negative δ_2. The finding also corroborated with previous studies conducted by Babalos *et al.* (2015) and Mand and Sifat (2021). The results in Table 5.9 also showed that δ_3 is significantly negative for the resource and service sectors which indicated that increases in interest rate is viewed as bad news by market participants and induces herding behaviour under high volatility regimes. δ_3 is also significantly positive for the industrial and resource sectors under the low volatility regimes which indicates that bad news in interest rate increase intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_4 is significantly negative for the resource and service sectors under the low volatility regimes which shows good news in interest rate decrease intensifies the market participants' divergence and reduces herding behaviour in these sectors. δ_4 is significantly positive for the whole market under the high volatility regime which also shows interest rate decrease is viewed as good news by market participants in these sectors and induce herding behaviour. This also supports the notion that market participants prefer to invest in stocks than in the banks when interest rates are very low.

δ_5 is significantly negative for the whole market (low volatility regime), Industrials sector (both low and high volatility regimes), Resources sector (high volatility regime), and services sector (low volatility regime). The results show that good news in ZAR appreciation intensifies the market participants' divergence and reduces herding behaviour in these sectors. However, δ_5 is also significantly positive for the resources sector under the low volatility regime which indicates ZAR appreciation is viewed as good news by the investors and induce herding behaviour in these sectors. δ_6 is significantly negative for the resources sector under the low volatility regime. This suggest ZAR depreciation is viewed as bad news by the investors and induce herding behaviour in the whole market and this sector. However, δ_6 is significantly positive for the Whole market (low volatility regime), financials sector (both low and high volatility regime), Industrials sector (low volatility regime) and services sector (low volatility regime). This indicates that bad news in ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in these sectors.

δ_7 is significantly positive for the resource and service sectors under the low volatility and high volatility regimes, respectively, which indicated that the extreme changes in ZAR appreciation is seen as good news by the investors and induce herding behaviour. However, δ_7 is also significantly negative for the whole market (low volatility regime), financials sector (low volatility regime), Industrials sector (both low and high volatility regimes) and Services sector (low volatility regime). This indicates that good news in the extreme changes in ZAR appreciation intensifies the market participants' divergence and reduces herding behaviour in these sector. δ_8 is significantly positive for the Resources sector (both low and high volatility regimes) and Services sector (low volatility regime). This indicated that bad news in the extreme changes in ZAR depreciation intensifies the market participants' divergence and reduces herding behaviour in this sector. δ_{82} is significantly negative for the financial and industrial sectors which indicates that the extreme changes in ZAR depreciation is seen as bad news by the investors and induce herding behaviour in these sectors during the low volatility regime consistent with Gong and Dai (2017).

Table 5.9 also provides expected durations of the market regimes. The high volatility regimes tend to be the most persistent as indicated by the longest average regime duration. The average regime duration for the high volatility state ranges from 1.38 months for the whole market to 17.42 for the financials sector. Low volatility regimes are more persistent in the resource and service sectors. This also underscores the significance of having hedging instruments to cushion volatility in these sectors. The average shortest regime durations for both low and high volatility regimes is observed under the financial and Industrial sectors, respectively, thereby implying more frequent regime switching in these sectors. This also shows that these two sectors are more volatile as compared to others.

Figures 5.1 through 5.20 below depicts market returns and smoothed probability plots for visual inspection of the dynamic nature of the state transitions and herding behavior for the whole market and various sectors. The smoothed probability plots suggested prevalence of the herding behaviour during the 2008-09 Global Financial Crisis period. The smoothed probability plots in Figures 5.1 through 5.20 tend to suggest a low-high (LH) volatility transition order whereby low volatility regime is followed by the high volatility regime. Thus, the low volatility regime plays as a signal warning to the market regulators before the high-volatility regime. Furthermore, there is a suggestion of a bi-directional transitions as shown by the smoothed probability regimes between the low and high volatility regimes. Thus, market regulators can play a pivotal role during stress periods in avoiding possible transitions to high volatility regimes.

5.6 Conclusions and policy implications

This study examines whether changes in two important South African macroeconomic variables, that is, changes in interest rates and exchange rates induces herding behaviour in the Namibian Securities Exchange (NSX). The empirical results of the time-varying transition probability 2-Regime Markov Switching model revealed evidence of herding behaviour for all equity stocks. On a sectoral level, herding behaviour is found under the financial, industrial and resource sectors. This study found mixed results with the regard to the effect of changes in interest rate and exchange rates on herding behaviour in the NSX. The results showed that bad news in the interest rate amplified herding behaviour on one hand and also intensifies the market participants' divergence and weakened it under the whole market, industrial and Resource sectors. However, under the financials sector, bad news in interest rate increase intensifies the market participants' divergence and weakens it. Good news in the decrease in interest rate amplified herding behaviour on one hand and also intensified the market participants' divergence and weakened it for the whole market, industrial and resource sectors. However, under the financials sector, good news in interest rate decrease also intensifies the market participants' divergence and reduces it.

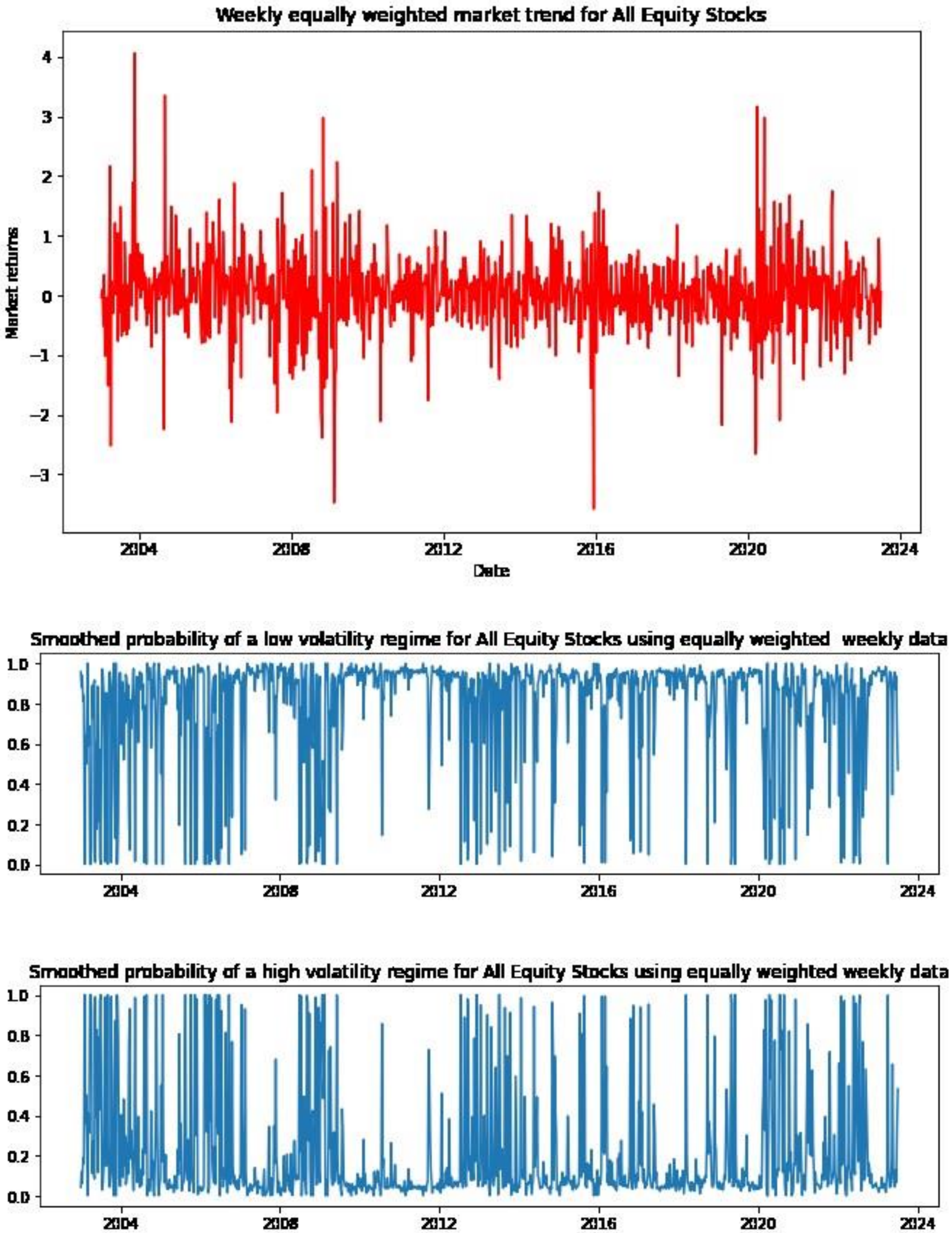
ZAR appreciation reveal mixed results. Good news in ZAR appreciation amplified herding behaviour on one hand and also intensified the market participants' divergence on the other hand and weakened it under the whole market and all the sectors, save for the financials sector. Under the financials sector, good news in ZAR appreciation only intensifies the market participants' divergence and weakened it. Bad news in the ZAR depreciation amplified herding behaviour on one hand and on the other hand weakened it by intensifying the market participants' divergence for the whole market and all the sectors.

This study also investigate the effect of extreme exchange rate volatility on herding behaviour in the NSX. The results of the 2-Regime Markov Switching model revealed that good news in the extreme changes in ZAR appreciation amplified herding behaviour on one hand and on the other hand also intensified the market participants' divergence on and weakens it for the whole market and all the sectors. Bad news in the extreme changes in ZAR depreciation also amplified herding behaviour on one hand and on the other hand weakened it by intensifying the market participants' divergence for all the sectors, save for the whole market.

The empirical findings in this study provides pivotal implications for both market participants and policy makers. Firstly, the NSX is highly integrated to other global stock markets like the Johannesburg Stock Exchange (JSE) with a number of stocks dually listed on these stock markets. Furthermore, the Namibian dollar (NAD) is pegged with the South African Rand (ZAR) at par. In this regard, capital inflows and outflows will be large between the countries and the task of achieving financial stability by the central banks and financial market regulators becomes more convoluted. Thus, coordination and synergy of monetary policies between the Republic of Namibia and Republic of South African (RSA), should be strengthen since changes in interest rates and exchange rates in South Africa influence herding behaviour in the NSX.

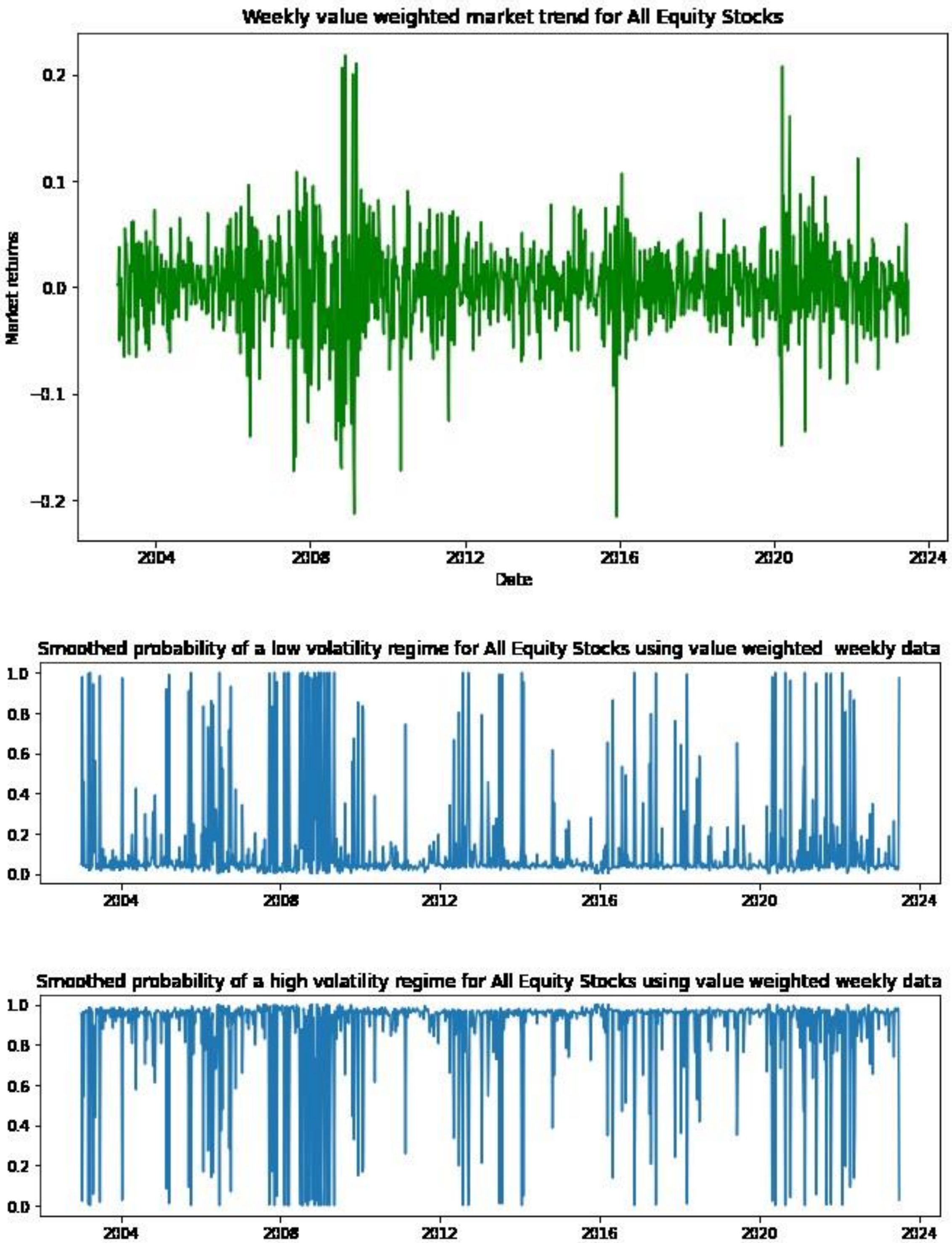
Secondly, changes in South African macroeconomic variables, that is, changes in interest rates and exchange rates should be monitored regularly by the Namibian financial market regulators. This may be useful in generating warning signals concerning the volatility regime the NSX may be transitioning into. Thirdly, the Namibian policymakers should also strengthen communications and coordination with the financial market regulators as changes in macroeconomic policies like interest rates and exchanges leads to herding behaviour in the entire market and the sectors. Future studies should also consider the effect of policy announcements and other South African macroeconomic variables on herding behaviour in the NSX. Apart from this, future studies should also consider examining spurious and intentional herding behaviour in the NSX.

Figure 5.1: Returns and smoothed probabilities for all equity stocks using the weekly equally weighted data



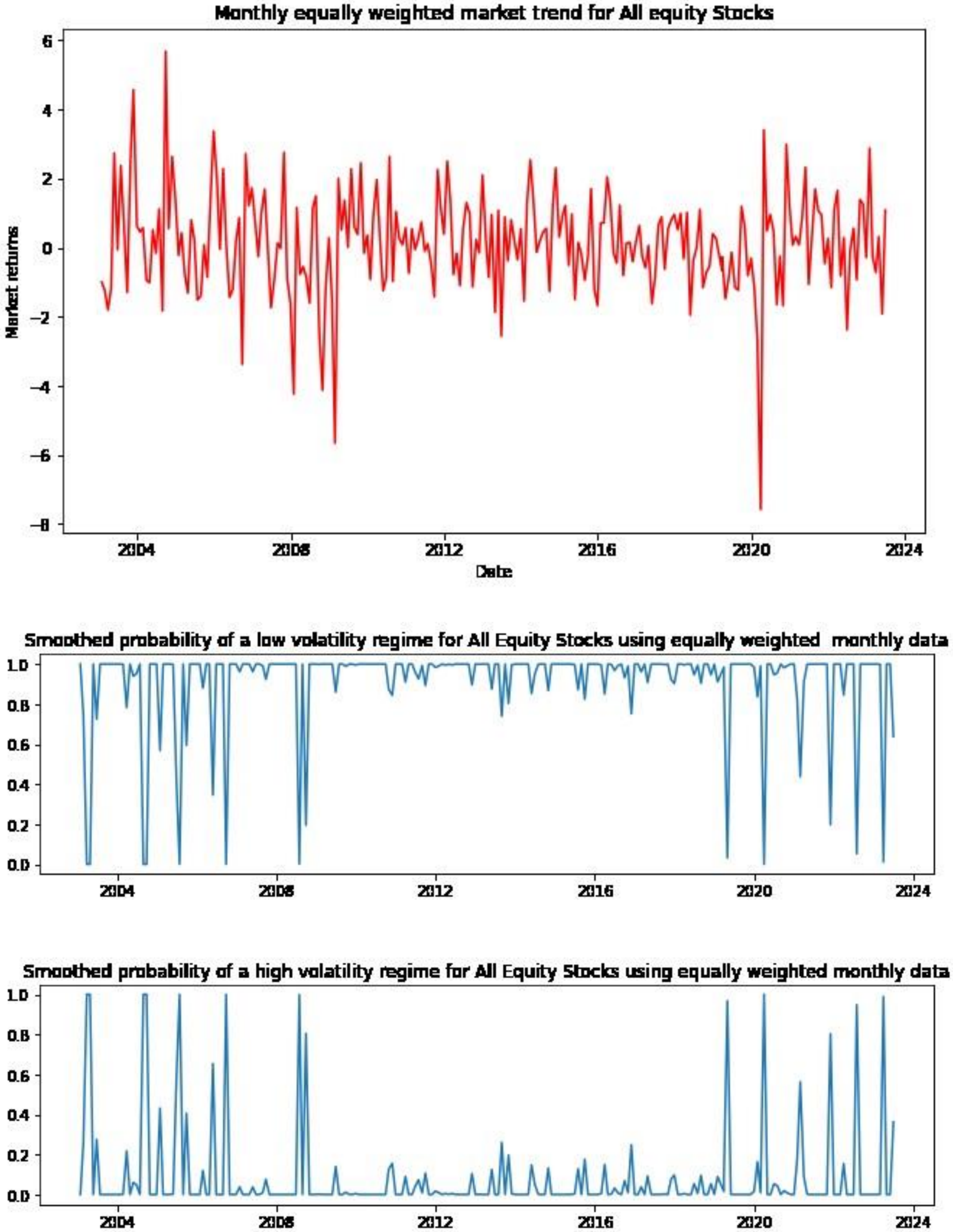
Source: Python results (2024)

Figure 5.2: Returns and smoothed probabilities for All Equity stocks using the weekly value weighted data



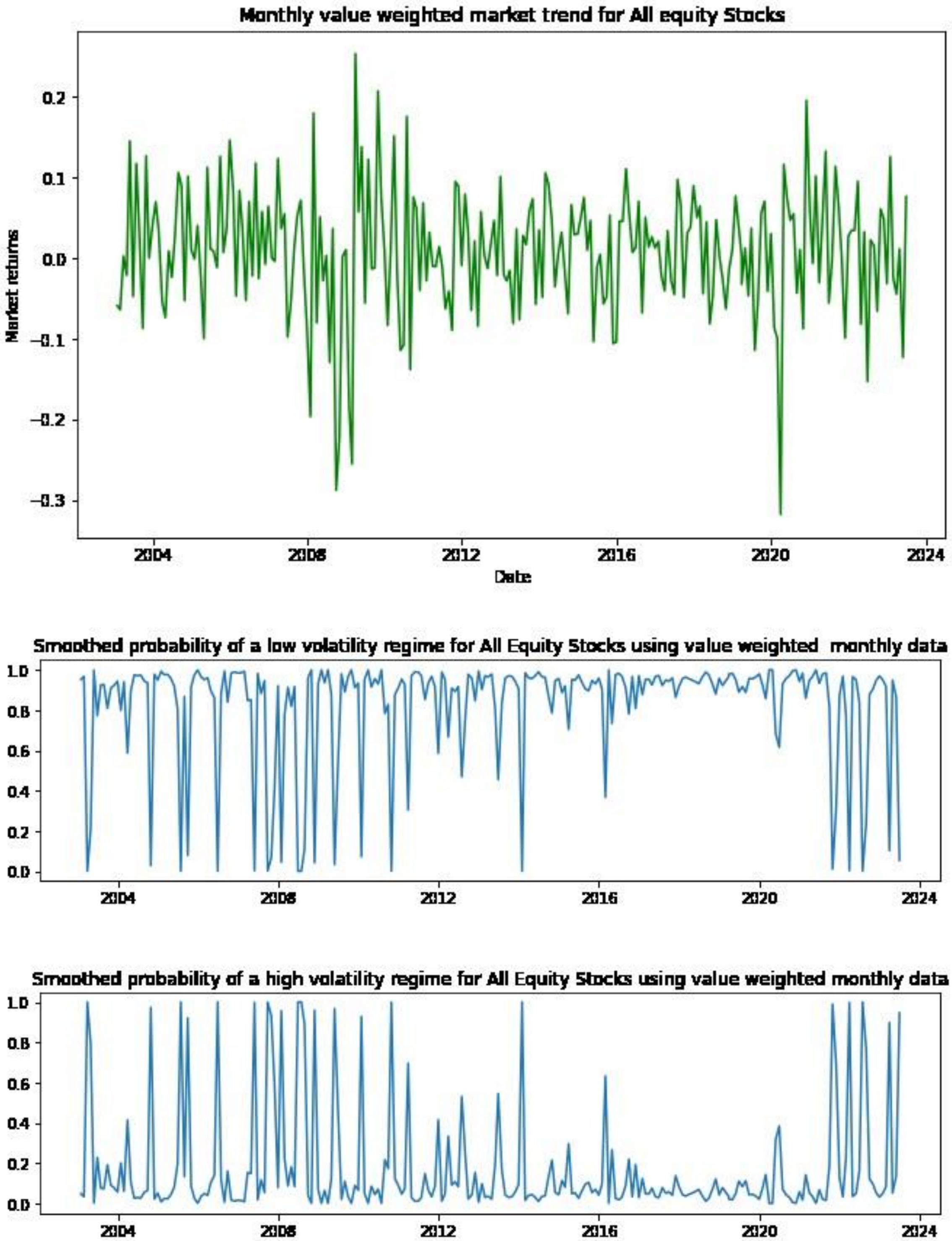
Source: Python results (2024)

Figure 5.3: Returns and smoothed probabilities for All Equity stocks using the monthly equally weighted data



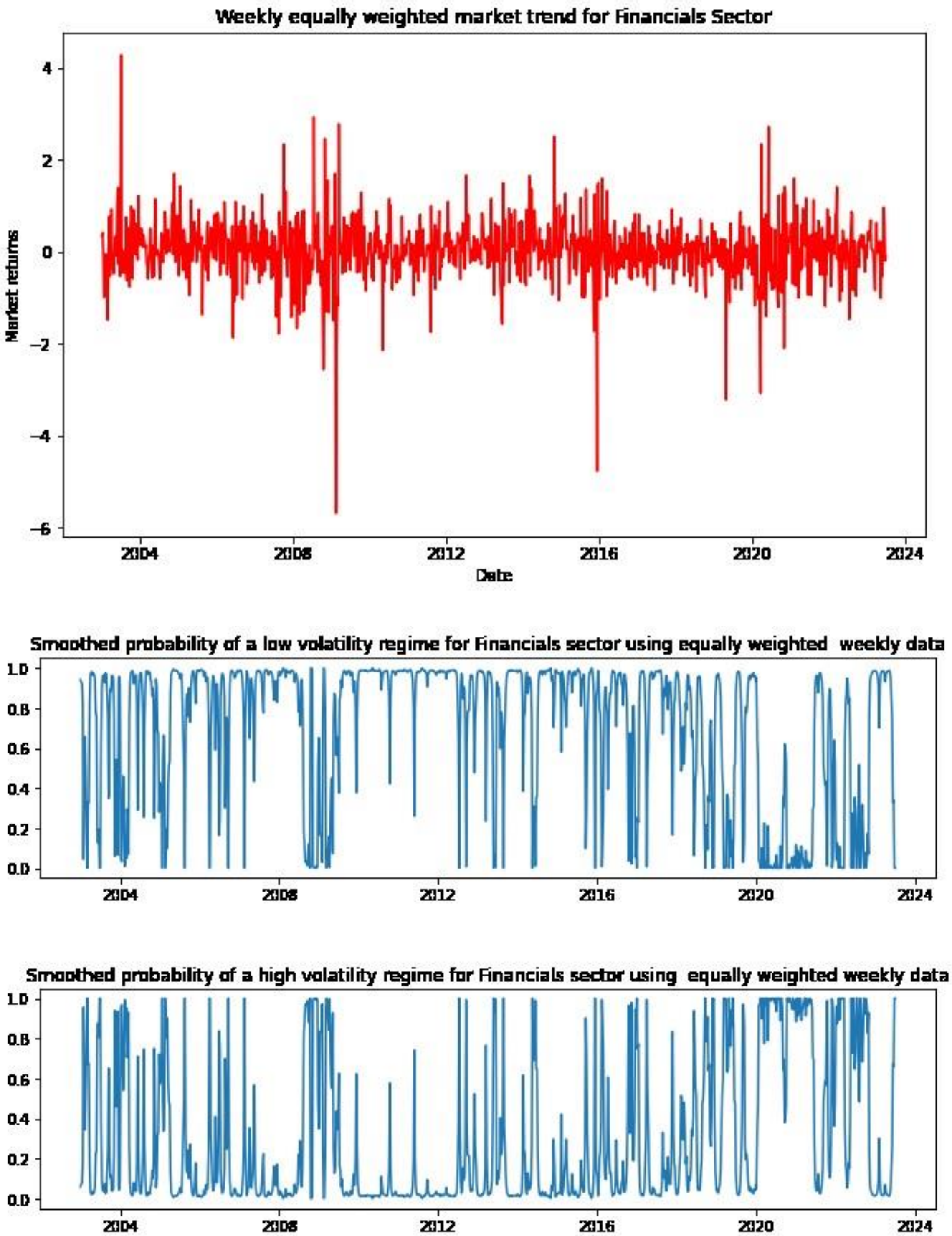
Source: Python results (2024)

Figure 5.4: Returns and smoothed probabilities for All Equity stocks using the monthly value weighted data



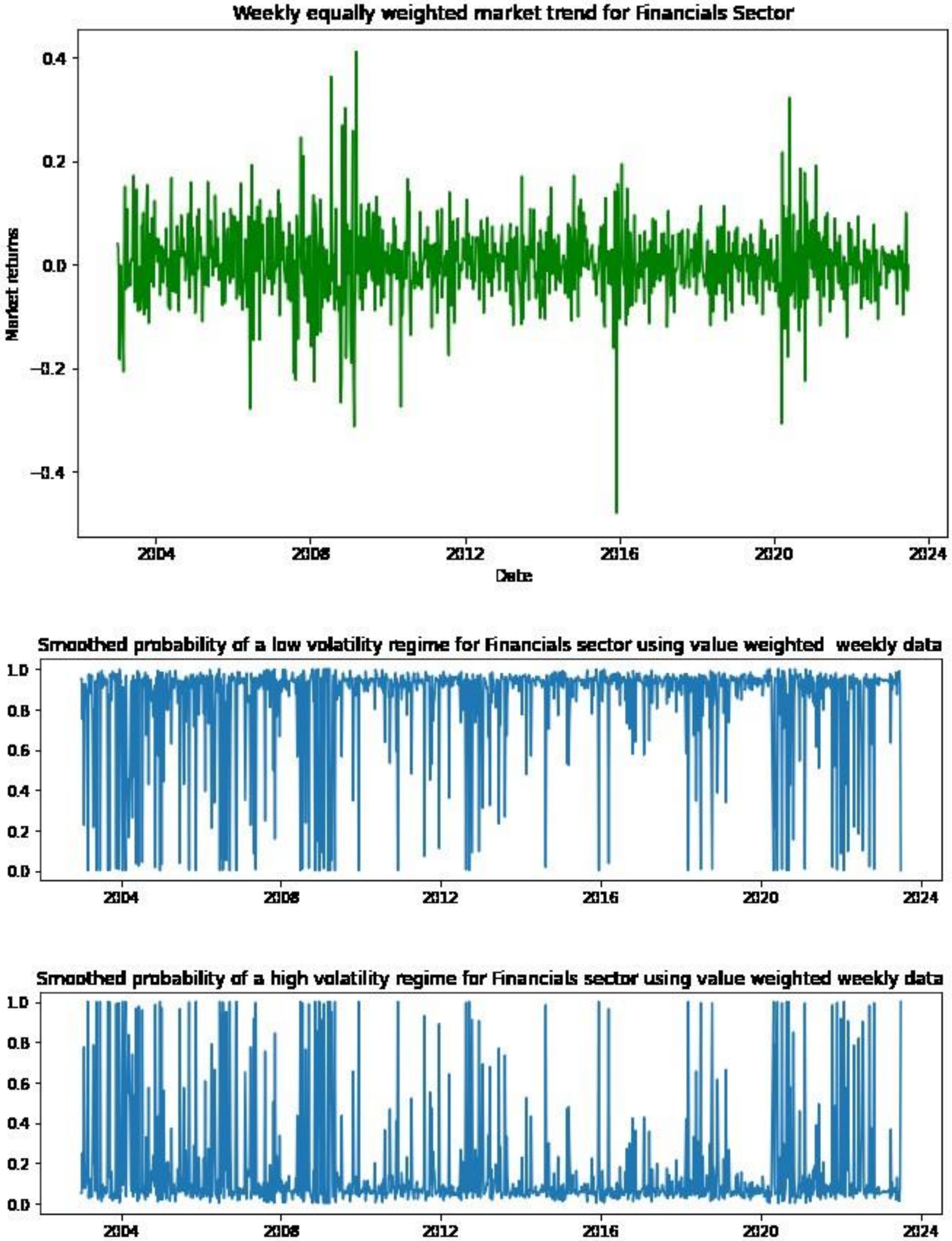
Source: Python results (2024)

Figure 5.5: Returns and smoothed probabilities for the Financials Sector using the weekly equally weighted data



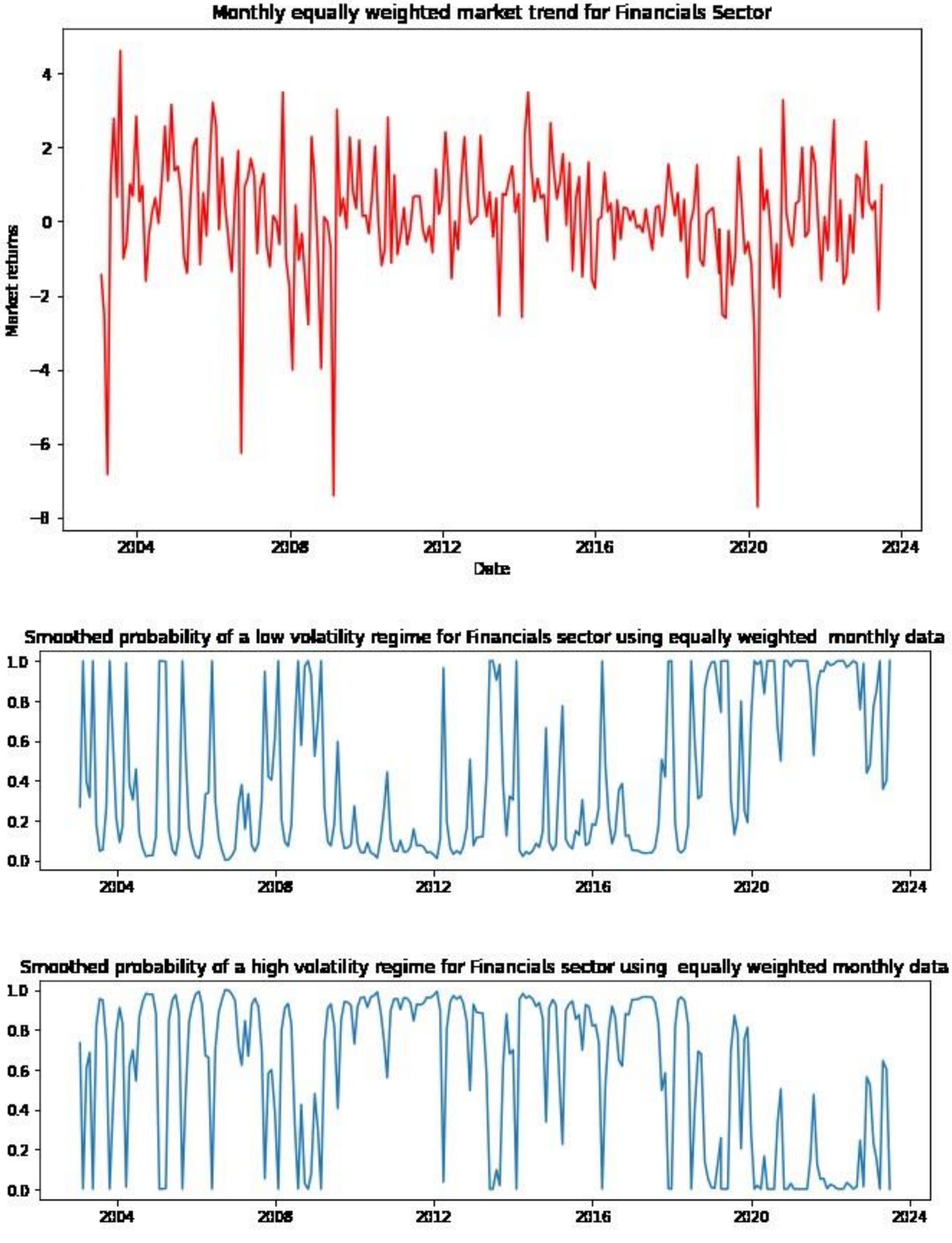
Source: Python results (2024)

Figure 5.6: Returns and smoothed probabilities for the Financials Sector using the weekly value weighted data



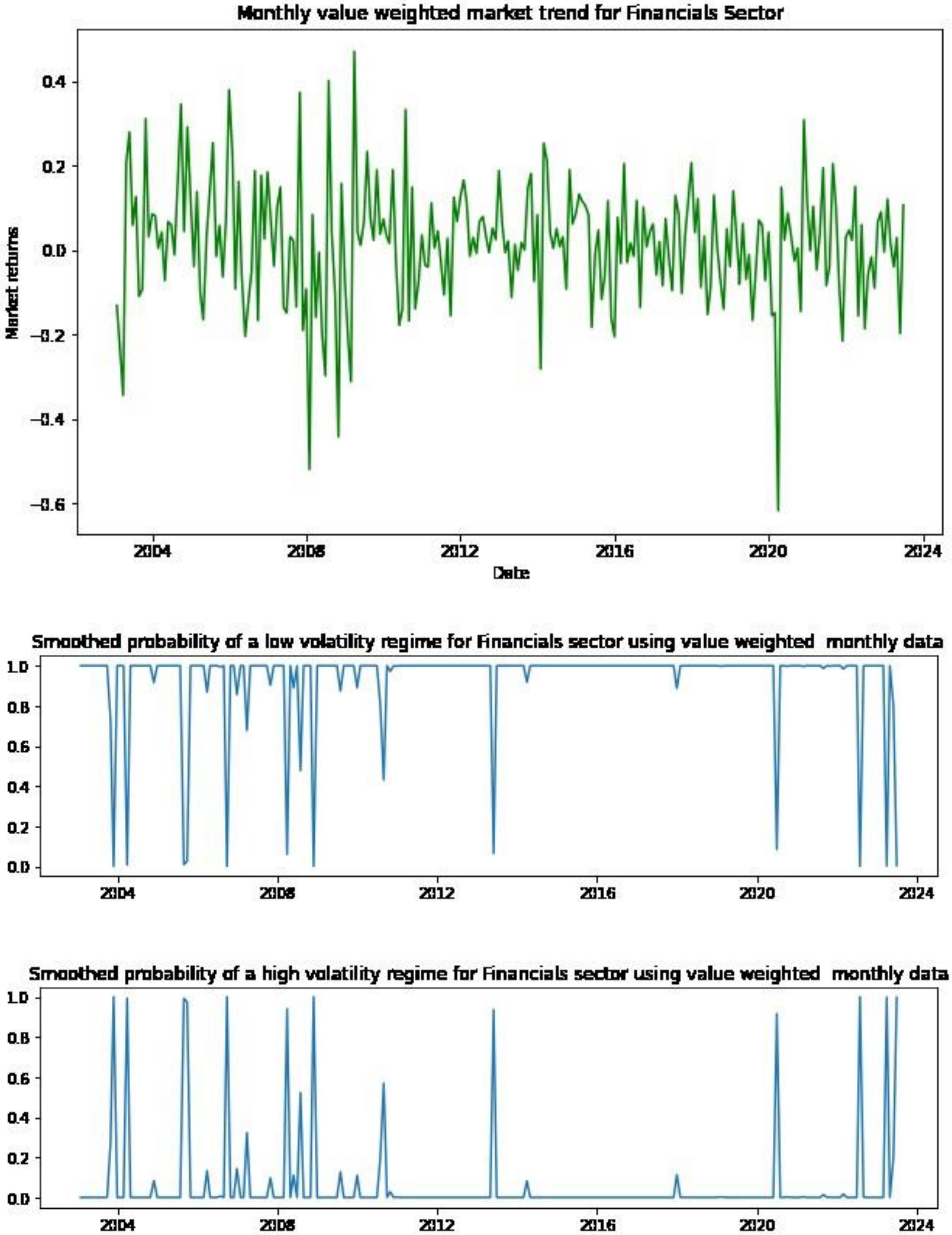
Source: Python results (2024)

Figure 5.7: Returns and smoothed probabilities for the Financials Sector using the monthly equally weighted data



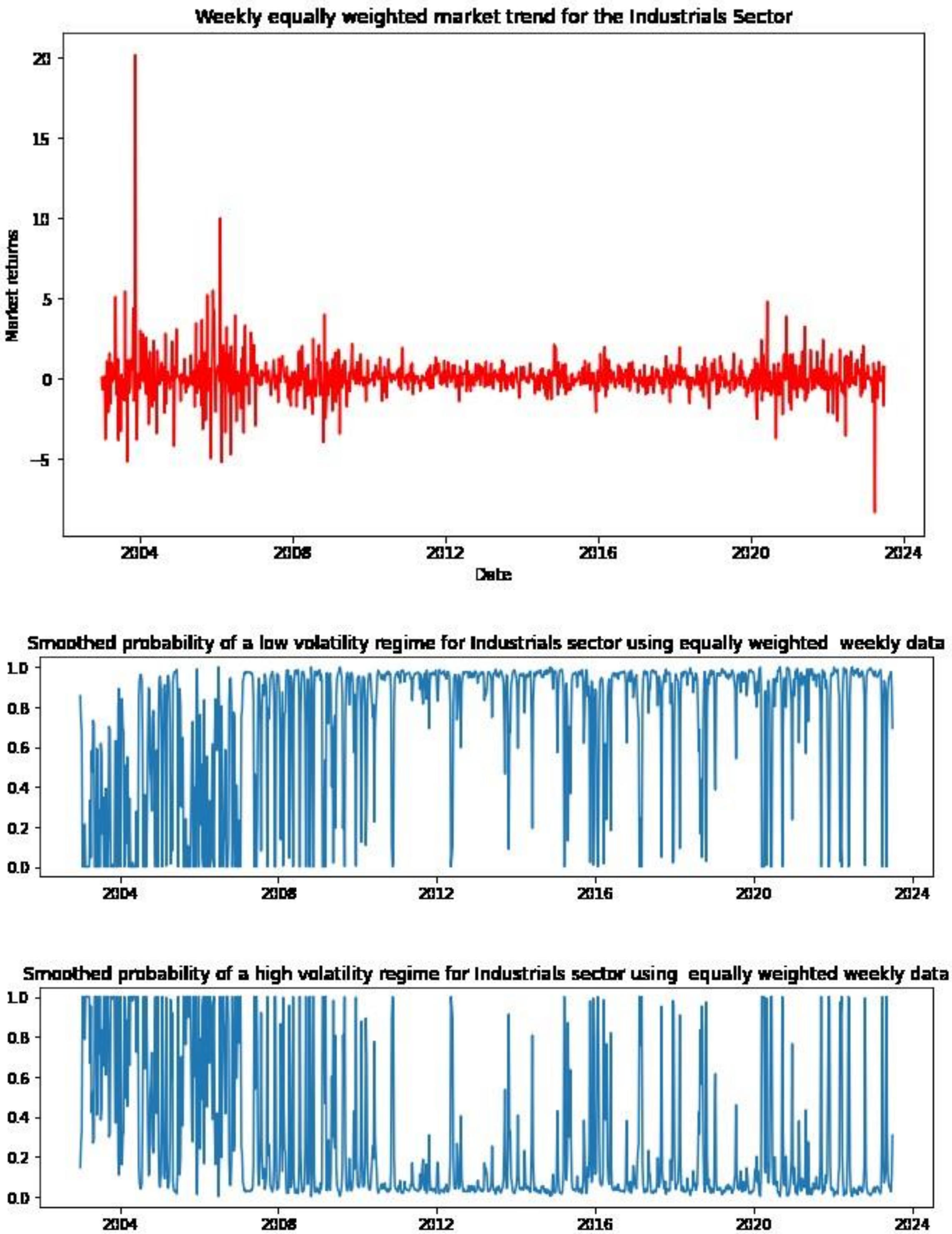
Source: Python results (2024)

Figure 5.8: Returns and smoothed probabilities for the Financials Sector using the monthly value weighted data



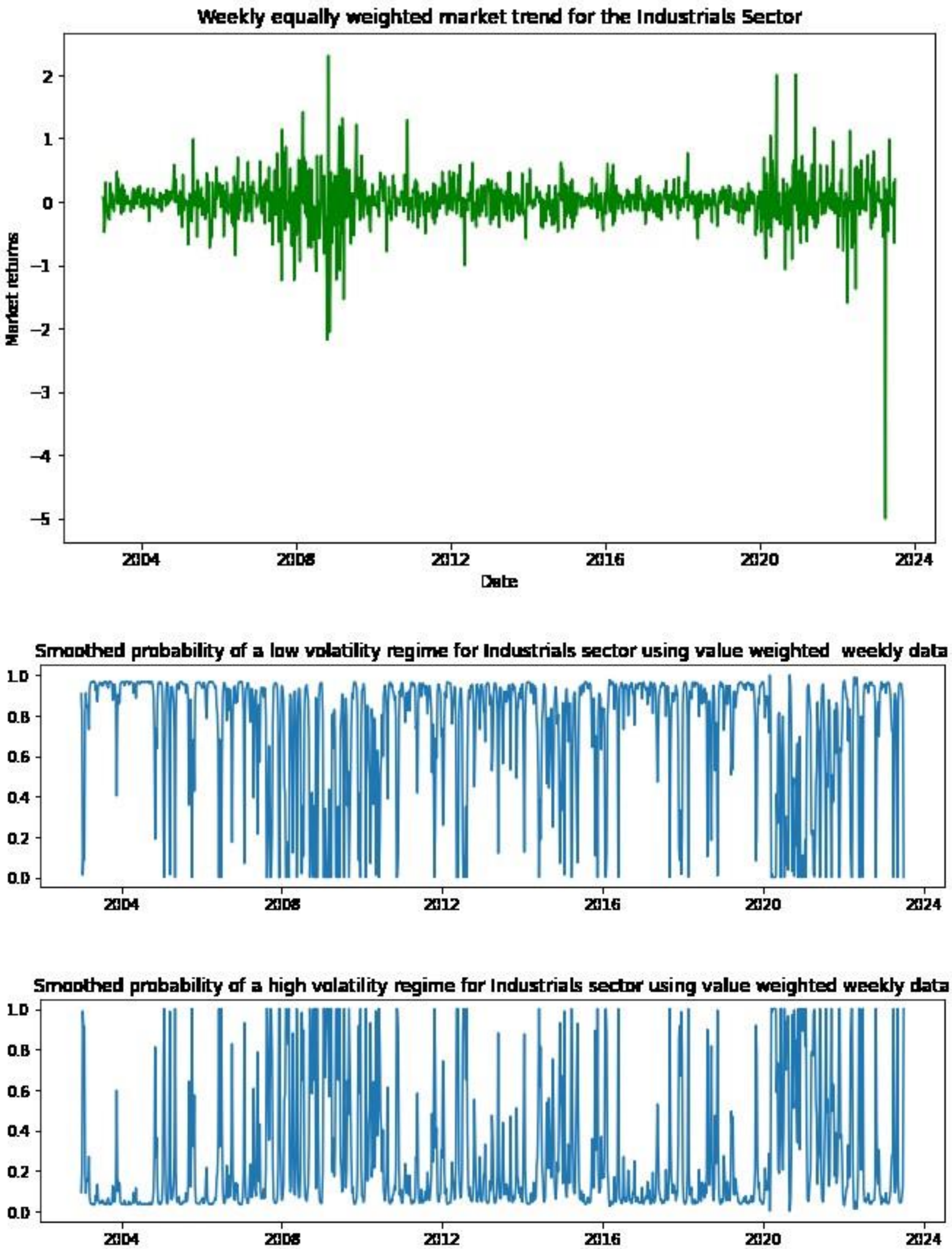
Source: Python results (2024)

Figure 5.9: Returns and smoothed probabilities for the Industrials Sector using the weekly equally weighted data



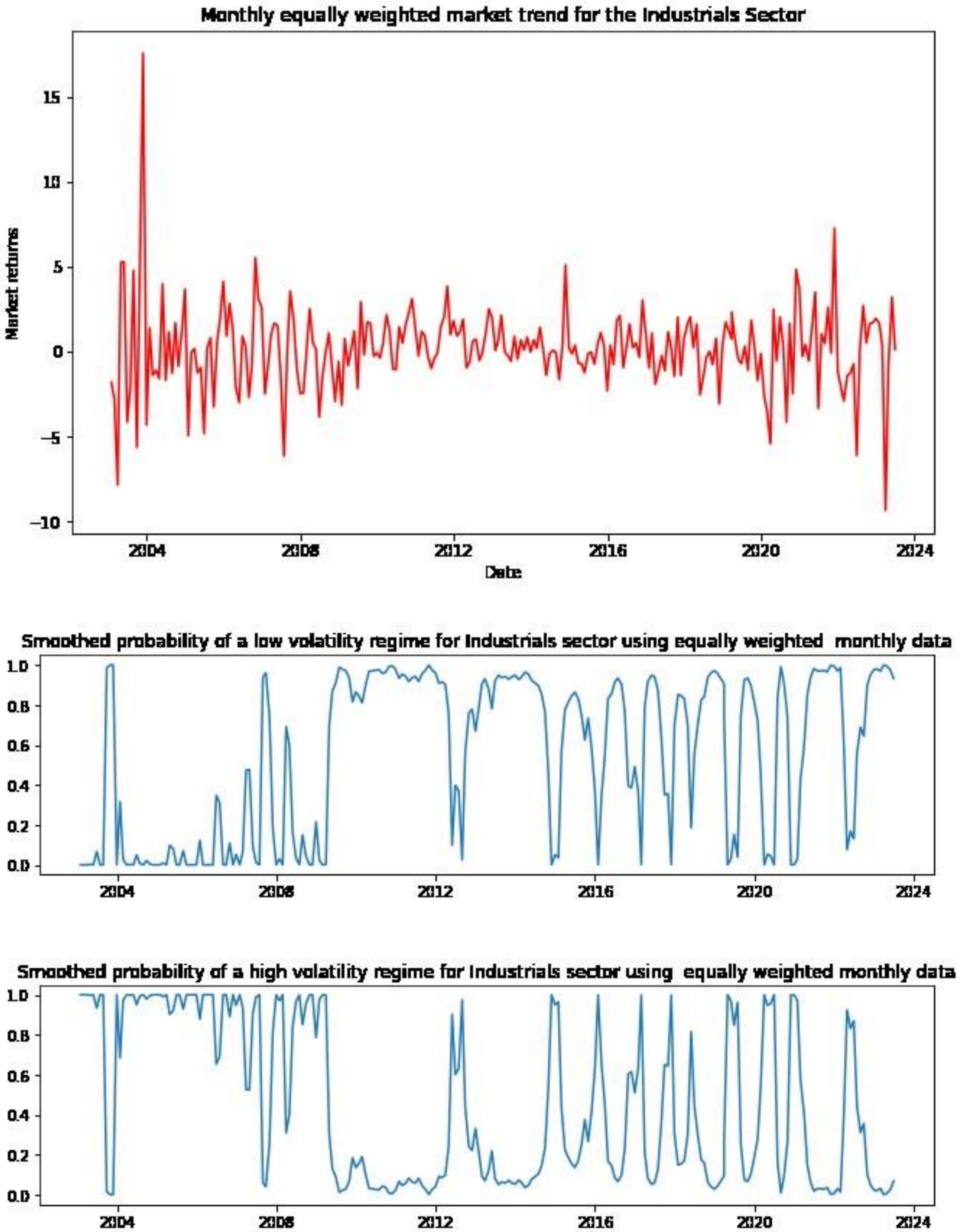
Source: Python results (2024)

Figure 5.10: Returns and smoothed probabilities for the Industrials Sector using the weekly value weighted data



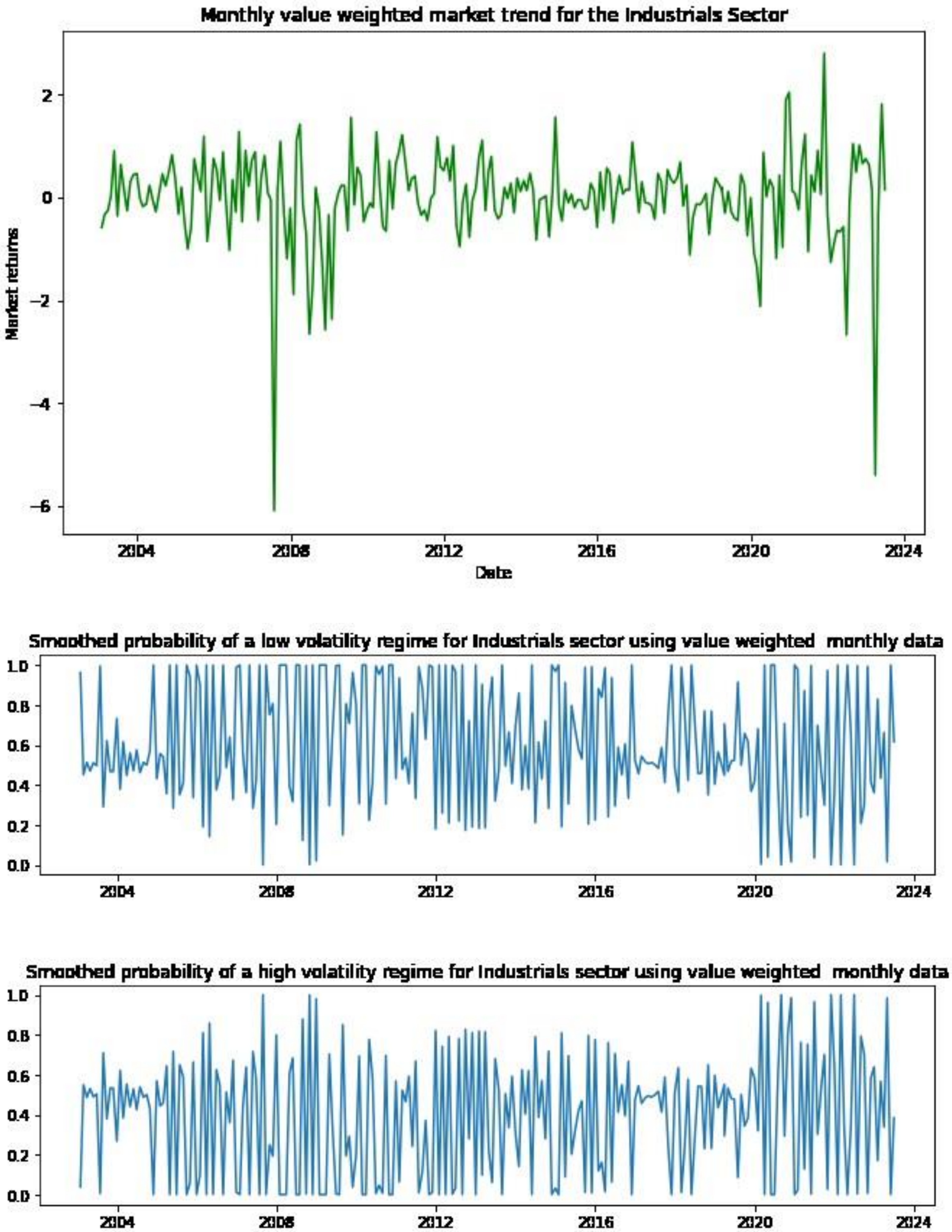
Source: Python results (2024)

Figure 5.11: Returns and smoothed probabilities for the Industrials Sector using the monthly equally weighted data



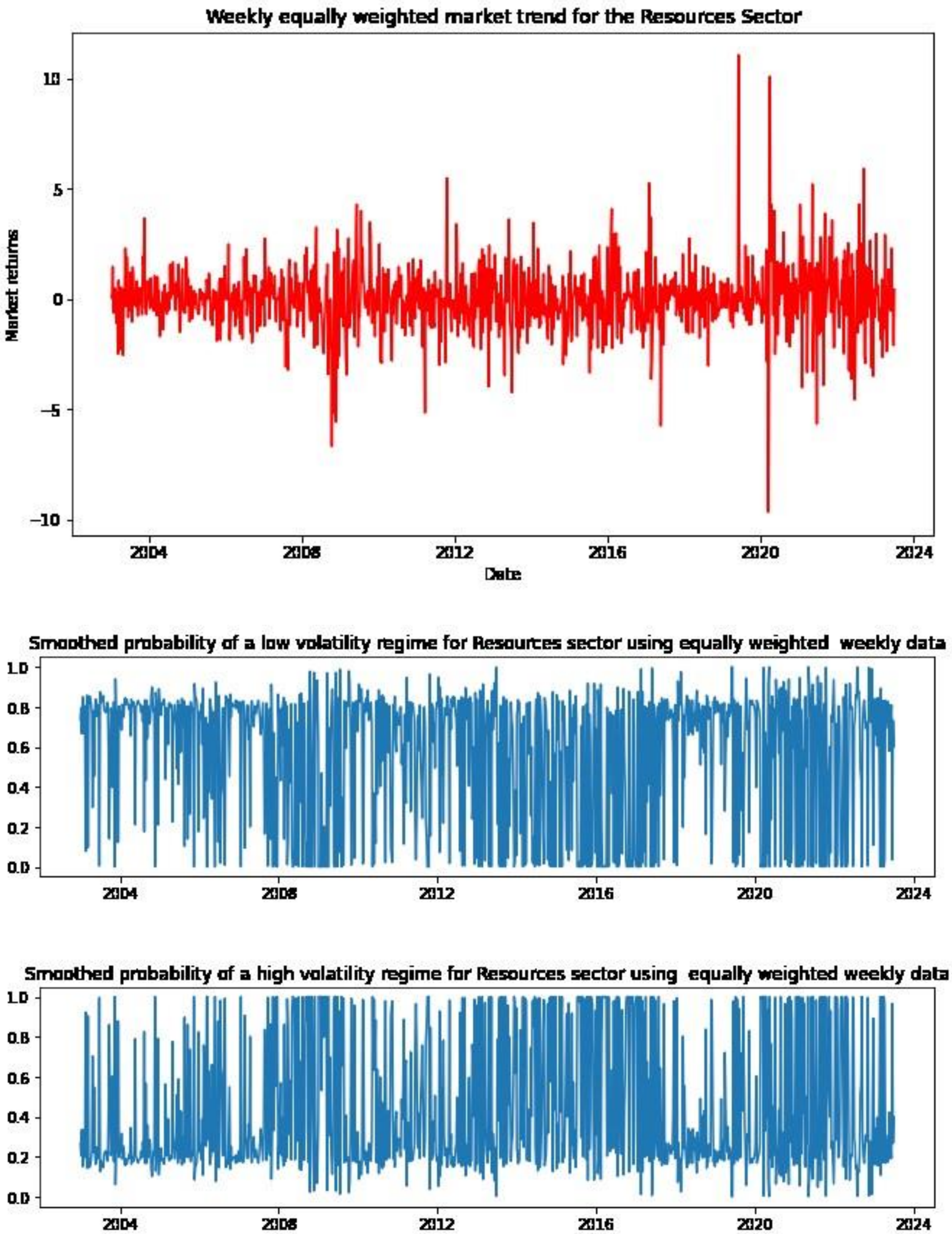
Source: Python results (2024)

Figure 5.12: Returns and smoothed probabilities for the Industrials Sector using the monthly value weighted data



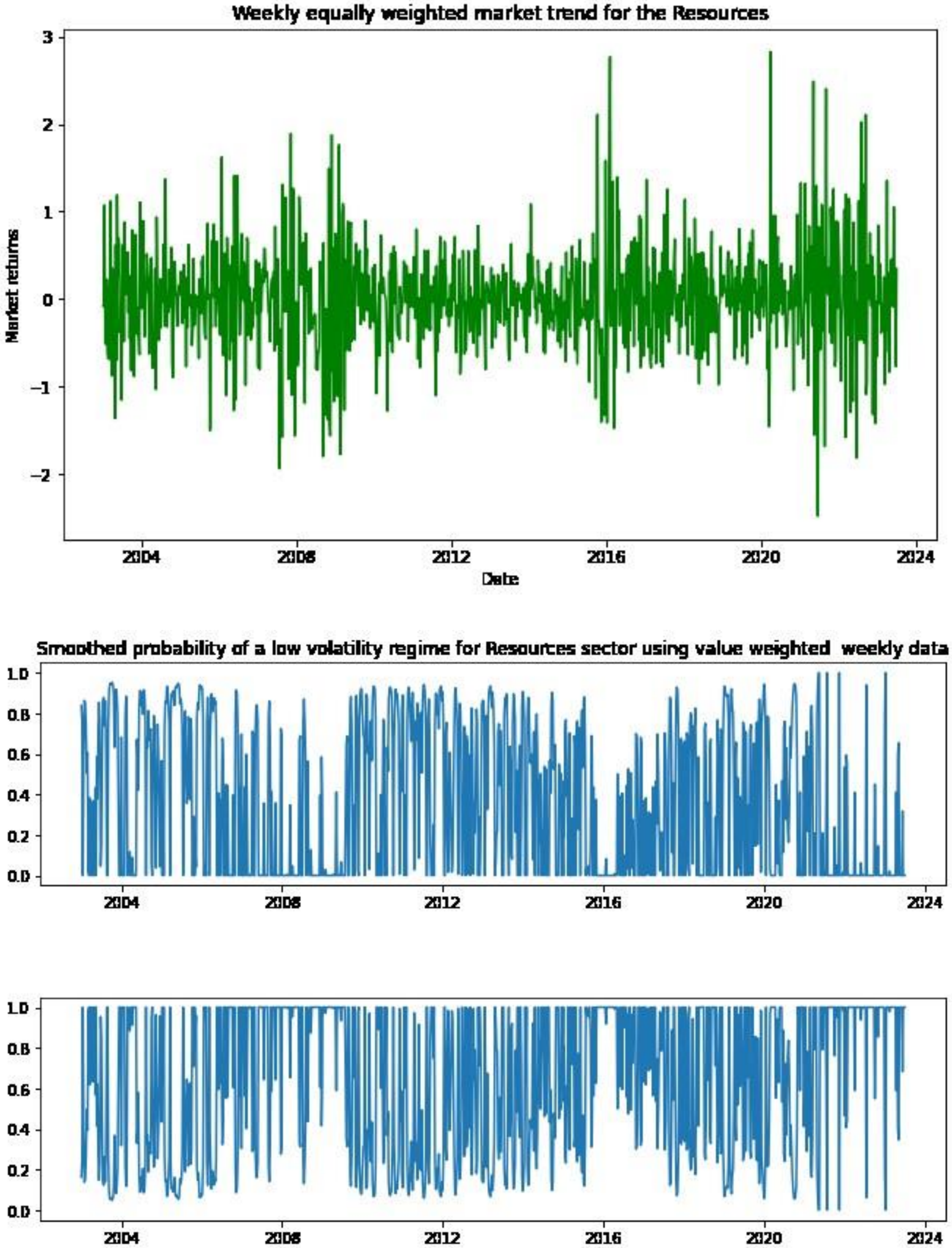
Source: Python results (2024)

Figure 5.13: Returns and smoothed probabilities for the Resources Sector using the weekly equally weighted data



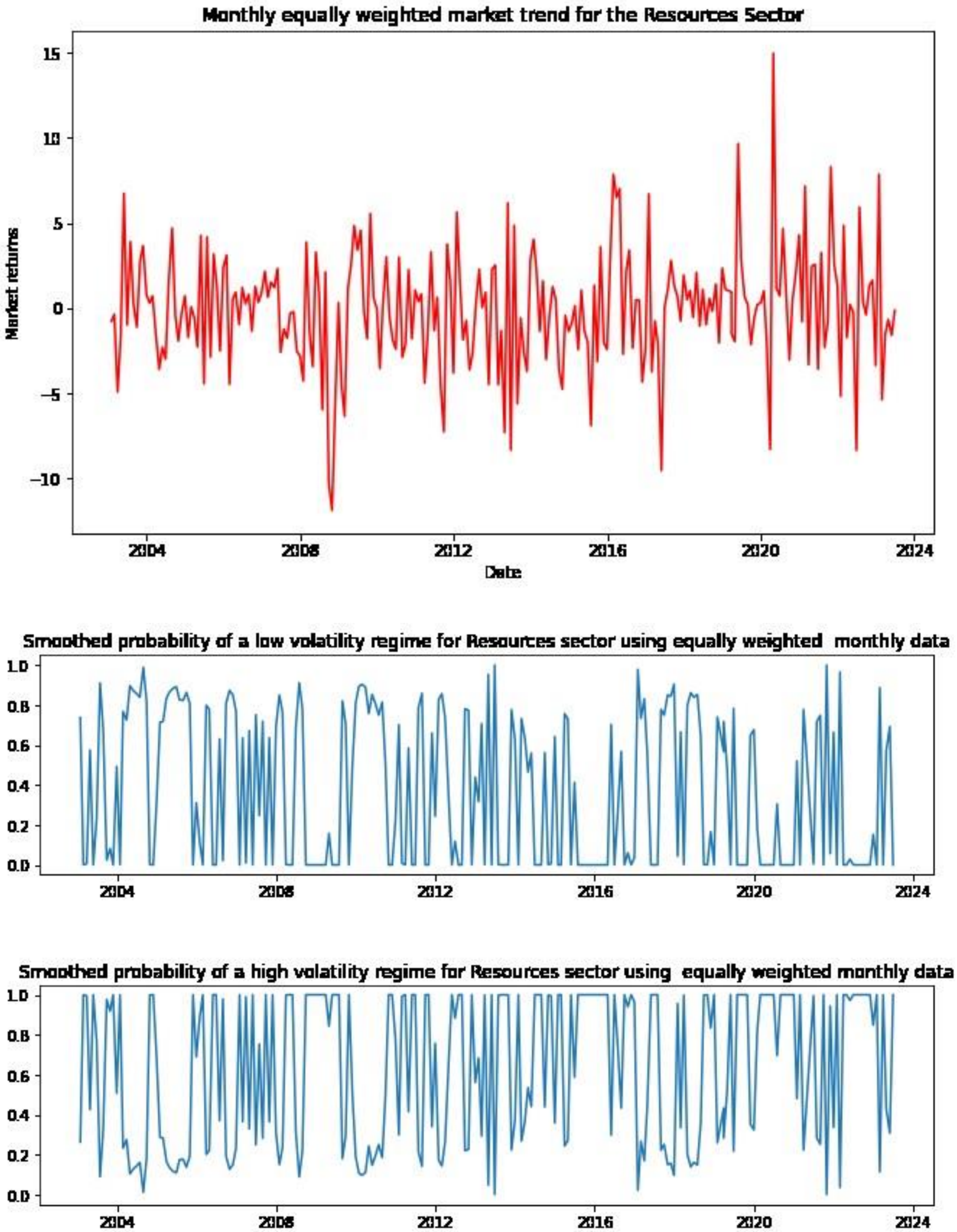
Source: Python results (2024)

Figure 5.14: Returns and smoothed probabilities for the Resources Sector using the weekly value weighted data



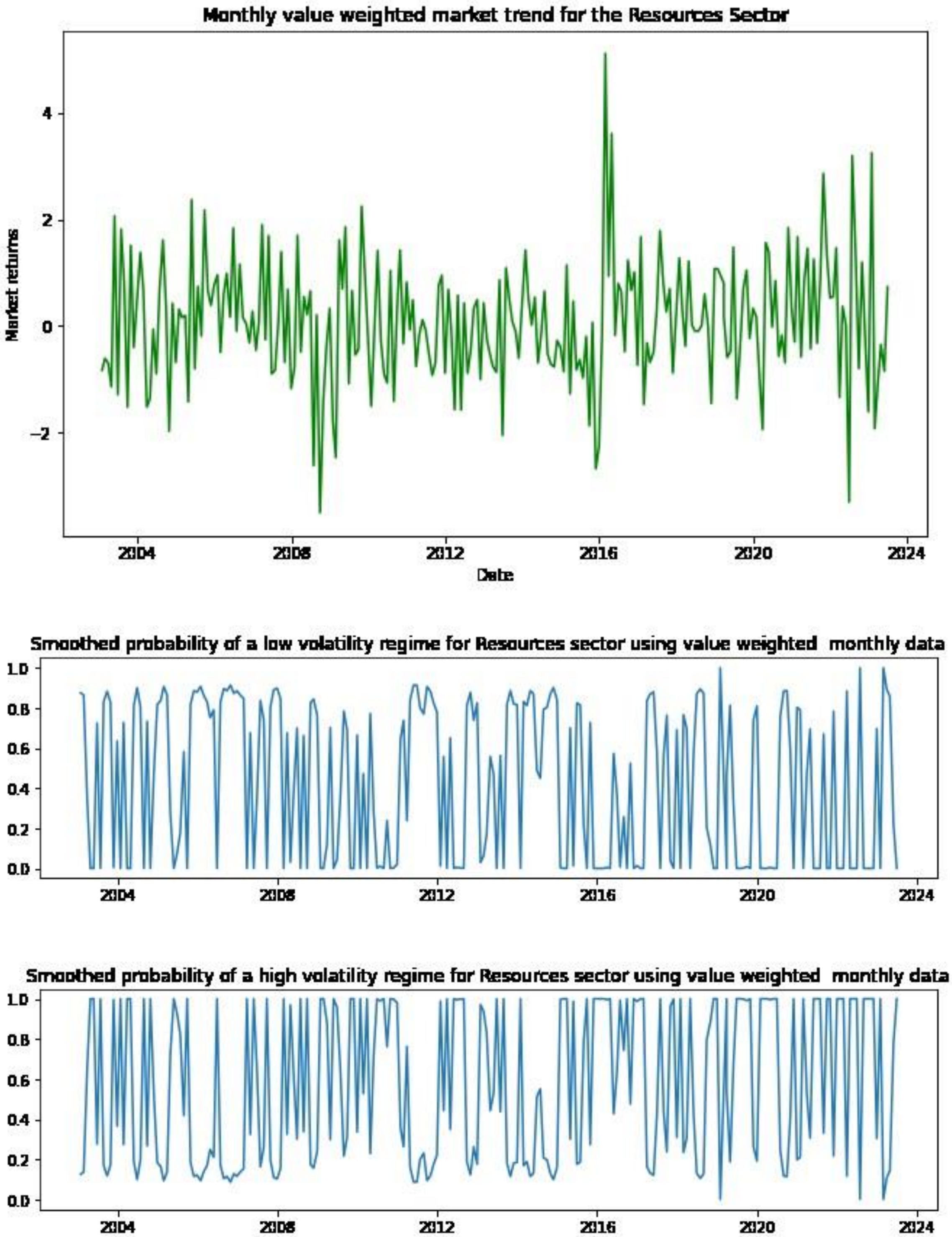
Source: Python results (2024)

Figure 5.15: Returns and smoothed probabilities for the Resources Sector using the monthly equally weighted data



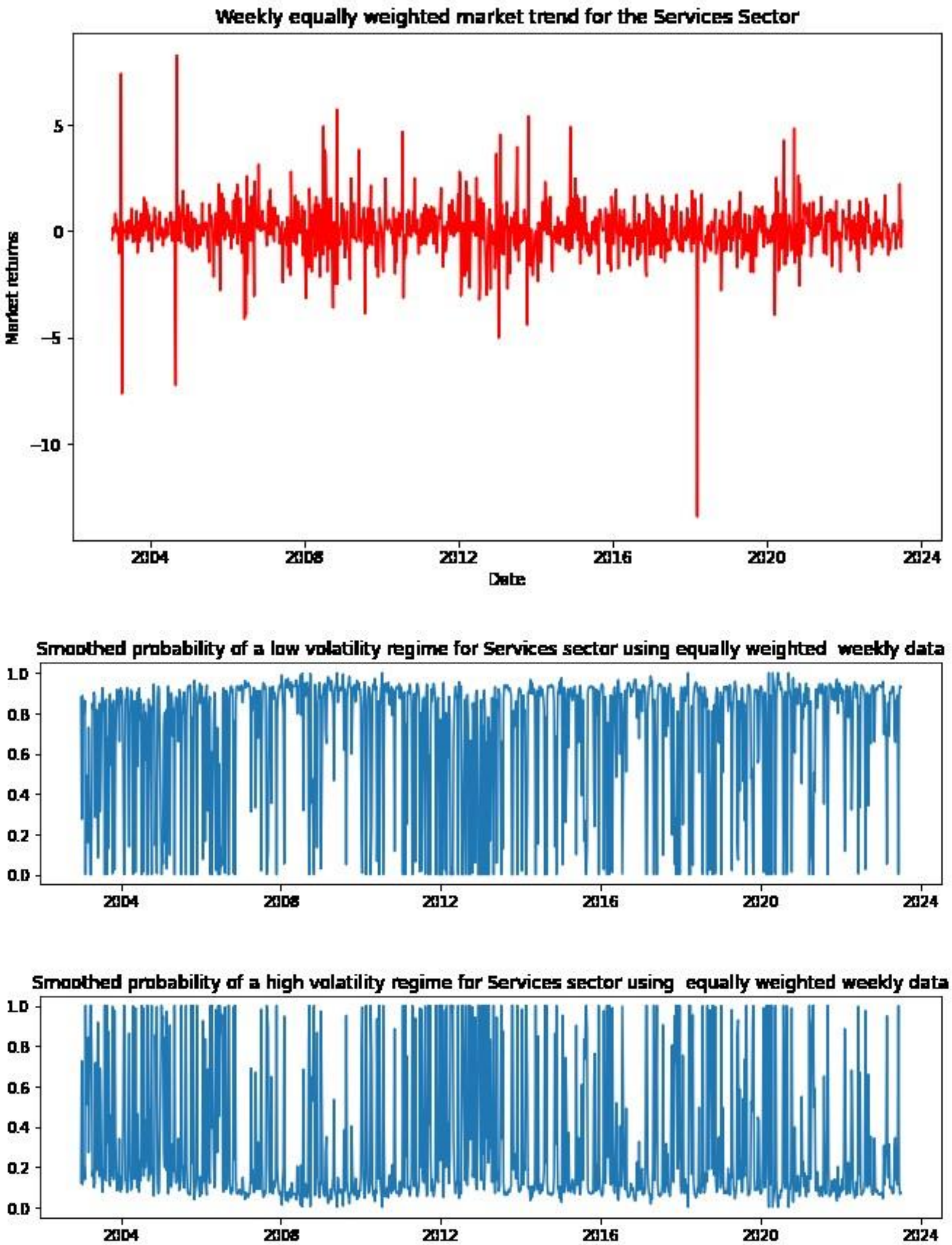
Source: Python results (2024)

Figure 5.16: Returns and smoothed probabilities for the Resources Sector using the monthly value weighted data



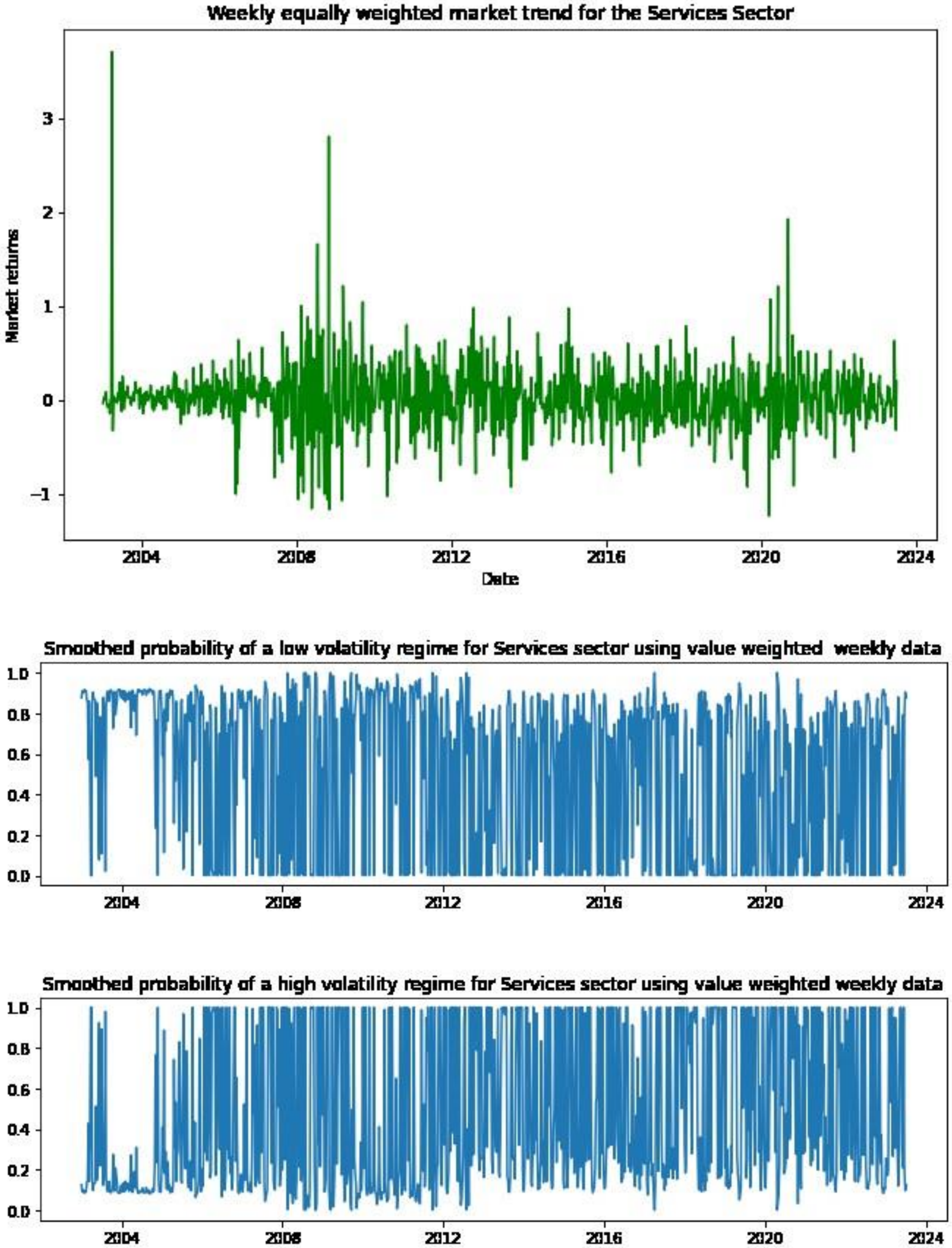
Source: Python results (2024)

Figure 5.17: Returns and smoothed probabilities for the Services Sector using the weekly equally weighted data



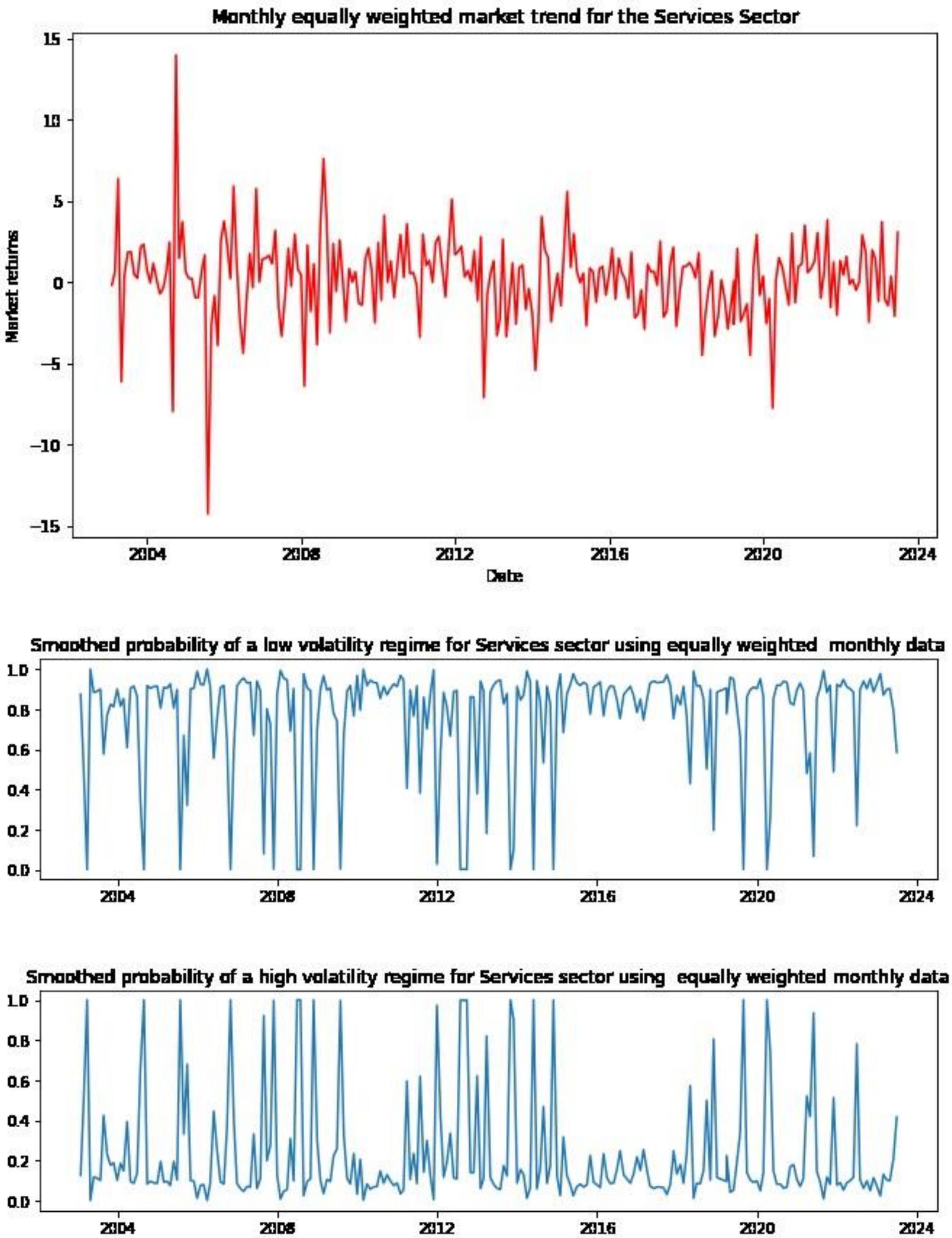
Source: Python results (2024)

Figure 5.18: Returns and smoothed probabilities for the Services Sector using the weekly value weighted data



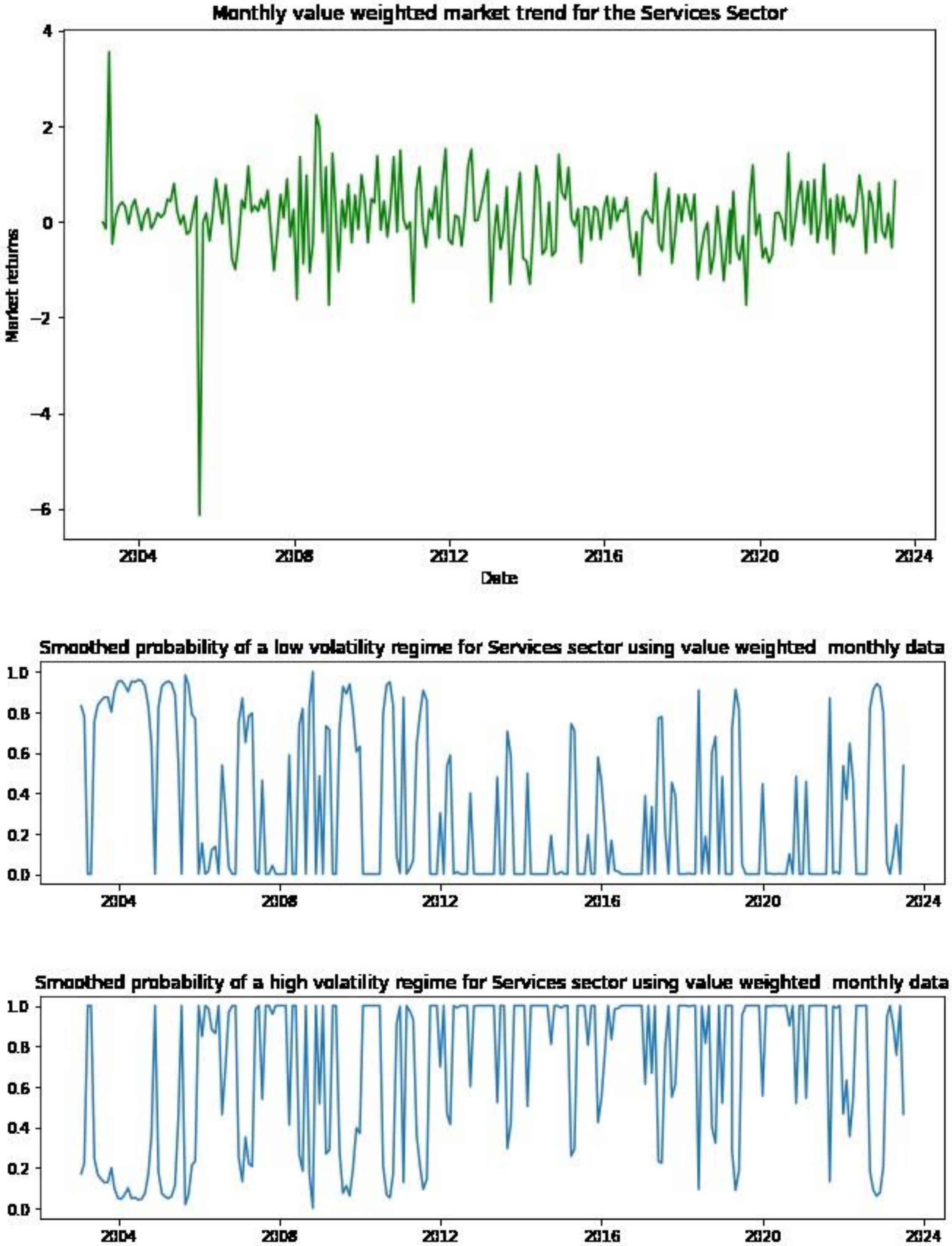
Source: Python results (2024)

Figure 5.19: Returns and smoothed probabilities for the Services Sector using the monthly equally weighted data



Source: Python results (2024)

Figure 5.20: Returns and smoothed probabilities for the Services Sector using the monthly value weighted data



Source: Python results (2024)

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Chapter 6: Conclusions

The main objective of this study was to examine herding behaviour dynamics in the Namibian Securities Exchange (NSX). The specific objectives of this study were therefore to: identify the existence of herding behaviour in the NSX; identify the existence of sectoral herding behaviour in the NSX; and examine the influence of South African macro-economic fluctuations on the herding behaviour in the NSX. This current study was motivated by a number of factors. Firstly, the existing literature on herding behaviour in the emerging markets is inconclusive and limited especially in Namibia. Thus, further investigation is required to provide more insight on the herding behaviour in the emerging markets particularly in the African context. Most of the existing literature on herding behaviour focuses on the developed markets, yet the phenomenon is believed to be more prominent in the emerging markets, due to stronger information asymmetry as pointed by Vo and Phan (2017) . This current research is the first one to analyse sectoral herding in the NSX. According to the researcher's knowledge, the only paper so far on the herding behaviour in the NSX by Guney *et al.* (2017) focuses on the whole market leaving the cross- sectoral idiosyncrasies untapped.

Secondly, the only paper highlighted above by Guney *et al.* (2017) uses the static approach which have some drawbacks. The current study transcended that approach and proposed the Markov-switching regime model (MRSM) which is able to capture time-varying phenomenon of herding behaviour, not only for the whole market but also from the sectoral perspective. Furthermore, due to globalisation, emerging stock markets are gradually playing a major role in the development of global financial markets.

Thirdly, since its inception in 1992 the NSX has witnessed low liquidity due to a number of factors, chief among them poor corporate governance of firms listed, regulatory constraints and poor quality of information relating to disclosure of financial statements (Matongela & Karodia, 2015). All these leads to lack of transparency in the NSX, as highlighted by Bikhchandani *et al.* (1992), as one of the major drivers of herding behaviour. Furthermore, the NSX is greatly affected by movements in other stock markets like the Johannesburg Stock Exchange (JSE), as most equities are dually listed on both the stock exchanges and therefore attracts a lot of investors. It is against all those mentioned characteristics that a further investigation is required to ascertain the presence and extend of the herding behaviour in the aforementioned equity market.

This current study was divided into papers following the three (3) specific objectives mentioned above. The first paper examines the existence of herding behaviour in the NSX for the period 1st January 2003 to 30th June 2023 using weekly and monthly data series. Equally and value weighted cross sectional and absolute standard deviation were used as an alternative measure of herding behaviour to the traditional cross-sectional standard deviation proposed by Christie and Huang (1995). As pointed by Lakonishok *et al.* (1992) herding behaviour tended to be pronounced in small firms than large firms due to poor flow of information in the former. To eliminate small the herding behaviour effect bias of small firms in a data series, the weekly and monthly stock returns in this research were weighted by the week-end and month-end total market capitalization of all the firms as done by Guney *et al.* (2017). The herding behaviour models in this research were first estimated using the static model and then using the Markov-switching regime model (MRSM), which is able to capture time-varying phenomenon of herding behaviour.

In all the estimation models, the static results points to a linear relationship between stock market dispersions as measured by the equally and value weighted CSAD and the stock market returns indicative of the absence of herding behaviour in the NSX for the period under review. However, herding behaviour is detected in high volatile regimes after utilising the MRSM, which is also consistent with previous researchers like Economou *et al.* (2016) and Chaffai and Medhioub (2018), who highlighted that herding behaviour tends to occur in high volatile due to hefty price movements and unpredictable market conditions. Thus, we can conclude the existence of herding behaviour in the NSX in the high volatile regimes which is consistent with some previous researchers.

The findings of the first paper may be of significance to the current and potential investors, management of firms listed on the NSX and Namibian policy makers. Firstly, the knowledge of herding behaviour may help current and potential investors in the NSX in the asset allocation process and diversification of risk, since herding behaviour often leads to market inefficiency. Secondly, management of firms listed on the NSX should improve transparency in terms of disclosure of published financial statements inorder to induce investors' confidence. Thirdly, Namibian policy makers should improve transparency in the NSX through sound legislative framework and afford equal opportunity to all investors in terms of vital communication for investment decision making.

The second paper examines the existence of sectoral herding behaviour in the NSX employing both the static models and dynamic models. The second paper finds inconsistent and conflicting results emanating from the two models. Based on the weekly and monthly data, the results of the static model revealed evidence of absence of herding behaviour for the sectoral level save for the industrials sector. However, the results of the two-state Markov switching-regime approach revealed non-linearity and existence of herding behaviour for the Industrial and Resource sectors especially during high volatility regime. The finding in this study implied that investors followed their own personal beliefs in tranquil regimes, but followed the actions of others during the more volatile regimes. In this regard, it is better to come up with a larger investment portfolio in order to reach the same diversification goal in more volatile states. Advancing literature on herding behaviour in the emerging markets, this study recommended future researchers to consider using high frequency data such as the daily data since herding behaviour is considered by many to a short to medium term phenomenon.

The third paper examines the influence of variations in South African interest rates and exchange rates on herding behaviour in the NSX using the time-varying transition probability Markov regime- switching model for the period 1st January 2003 to 30th June 2023. The empirical results of the time-varying transition probability 2-Regime Markov Switching model revealed evidence of herding behaviour for all equity stocks. On a sectoral level, herding behaviour is found under the financial, industrial and resource sectors. This study found mixed results with the regard to the effect of changes in interest rate and exchange rates on herding behaviour in the NSX. The results showed that bad news in the interest rate increase amplified herding behaviour on one hand and also intensified the market participants' divergence and weakened it under the whole market, industrial and resource sectors. However, under the financials sector, bad news in interest rate increase intensified the market participants' divergence and weakened it. Good news in the decrease in interest rate amplified herding behaviour on one hand and also intensified the market participants’ divergence and weakened it for the whole market, industrial and resource sectors. However, under the financials sector, good news in interest rate decrease also intensifies the market participants’ divergence and reduced it.

ZAR appreciation adduced mixed results. Good news in ZAR appreciation amplifies herding behaviour on one hand, and also intensifies the market participants’ divergence on the other hand and weakens it under the whole market and all the sectors, save for the financials sector. Under the financials sector, good news in ZAR appreciation only intensified the market participants’ divergence and weakened it. Bad news in the ZAR depreciation amplifies herding behaviour on one hand and on the other hand weakened it by intensifying the market participants’ divergence for the whole market and all the sectors.

This study also investigated the effect of extreme exchange rate volatility on herding behaviour in the NSX. The results of the MRSM revealed that good news in the extreme changes in ZAR appreciation amplified herding behaviour on one hand and on the other hand also intensifying the market participants’ divergence on and weakens it for the Whole market and all the sectors. Bad news in the extreme changes in ZAR depreciation also amplified herding behaviour on one hand and on the other hand weakened it by intensifying the market participants’ divergence for all the sectors, save for the whole market.

The empirical findings in the third paper provided pivotal implications for both market participants and policy makers. First, the NSX is highly integrated to other global stock markets like the Johannesburg Stock Exchange (JSE) with a number of stocks dually listed on these stock markets. Furthermore, the Namibian dollar (NAD) is pegged with the South African Rand (ZAR) at par. In this regard, capital inflows and outflows will be large between the countries and the task of achieving financial stability by the central banks and financial market regulators becomes more convoluted. Thus, coordination and synergy of monetary policies between the Republic of Namibia and Republic of South African (RSA) should be strengthen since changes in interest rates and exchange rates in South Africa influence herding behaviour in the NSX. Second, changes in South African macroeconomic variables, that is, changes in interest rates and exchange rates should be monitored regularly by the Namibian financial market regulators. This may be useful in generating warning signals concerning the volatility regime the NSX may be transitioning into.

Third, the Namibian policymakers should also strengthen communications and coordination with the financial market regulators as changes in macroeconomic policies like interest rates and exchanges leads to herding behaviour in the entire market. Future studies should also consider the effect of policy announcements and other South African macroeconomic variables on herd behaviour in the NSX. Apart from this, future studies should also consider examining spurious and intentional herd behaviour in the NSX.

The empirical and theoretical contribution of this current study is the utilisation of the time-varying transition probability Markov two-Regime Switching model (MRSM) in estimating herding behaviour in the NSX. The major benefits of the MRSM is that it is able to capture time-varying phenomenon of herding behaviour, which the static models fail to do. Furthermore, literature on herding behaviour especially in the African context is limited. Thus, this current research contributes greatly to the database of herding behaviour especially in the African context.

Despite the major contributions stated above, there are also some limitations regarding the herding measure used in this study. Therefore, future studies in the area of herding behaviour should also consider coming up with new herd measures that can capture "passive" or "silent" herding. The herding behaviour utilised in this study can only tests "active" herd behaviour whilst ignoring "passive" herd behaviour. Instinctively or naturally an investor would be regarded to have herded if he/she makes an investment decision not knowing the investment decision of others, but does not proceed with that investment decisions if he/she discovers that other investors have opted against doing so. The return dispersion herding measure looks at price clustering whilst ignoring "passive" herding, that is, the herd behaviour that can be conveyed when an investor makes an investment decision against proceeding with trading action after realising that others have made the same decision. Taking as an example, an investor who have chosen an equity for investment, but later realises others do not invest in that equity and avoid it. If that investor decides against proceeding with action and disregard his/her own belief, then that investor would be regarded as having herded. However, this "passive" or "silent" herd behaviour may not be picked in empirical investigation as it is difficult to measure.

Furthermore, future studies should also clearly state what form of herding behaviour will be investigated and devise appropriate methods to test each form of herding behaviour. This can perhaps help in resolving some inconsistences and inconclusiveness in herding behaviour empirical evidences. Future studies should also consider paying particular attention on the interaction between the different types of investors, for example, the interaction between the individual and institutional investors or between domestic and foreign investors considering that different types of investors may possess unique information and also responds differently to various financial markets signals.

Apart from this, more research should be carried in emerging equity markets at both individual and institutional level as well as untapped financial markets such as bond, derivatives, commodity, real estate markets among others. Future studies may also consider separating dual listed equities from the single ones. At last but not at least, significant constants in the regression results in this study points towards the need for potential additional variables. Thus, future researchers may consider adding variables in the regression such as dividends to see if the results will significantly differ.

Appendices

Appendix A: Exemption from Ethical Clearance

UNAM
UNIVERSITY OF NAMIBIA

Approval for Exemption from Ethical Clearance

Ethical clearance exemption reference No: DEC FOC/03/25
Review Date: 20/02/2025

Title of Project: **HERDING BEHAVIOUR DYNAMICS IN THE NAMIBIAN STOCK EXCHANGE (NSX)**

Student Name: HONEST DEMBURE

Student Number: 201101339
Supervisor(s): DR. J. de BEER

Dear Sir/Madam.

This letter certifies that the application for ethical clearance for the project stated above has been reviewed by the Faculty of Commerce, Management and Law Decentralized Ethics Committee (DEC). The Ethics Committee has given due consideration and concludes that the said proposal be exempted from review as it does not involve direct contact with human participants and in addition your study relies on secondary data which does not require ethical clearance. This is aligned with the University research ethics policy on ethical exemptions page no.16 (C1.3). Please note that any changes to the procedure must be brought to the notice of the DEC. The DEC must determine whether the requested procedure changes alter the risks.

Please contact the DEC office if you have any questions. Any correspondence with the DEC office regarding this action should mention the allocated Ethical clearance exemption reference number indicated at the top of this letter.

The ethics committee wishes you the best in your research.

Regards,

Precious Mushendami (FOC Decentralized Ethics Committee)

Prof. Davis Mumbengegwi (Head of MRS, Centre for Research Services)

Appendix B: Certificate of language editing

Dr Chakabwata William
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24/07/2024

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RE: Certificate of Language and copy editing

This certificate serves to confirm that I copyedited and proofread the thesis of Mr Honest Dembure titled 'Herding behaviour dynamics in the Namibian Stock Exchange' for the degree of Doctor of Philosophy in Economics at University of Namibia.

I declare that I professionally copyedited and proofread the thesis and removed errors spellings, grammar and punctuation. In some instances I improved sentence construction, without changing the content provided by the student. I also removed typographical errors, and ensured that the document was appropriately formatted in order to comply with the requirements of University of Namibia.

I am a competent language and copyeditor and have edited multiple academic work for students from diverse institutions in Namibia and those studying in regional institutions of higher learning.

Please feel free to contact me should the need arise.

Yours faithfully,

Chakabwata

Dr Chakabwata William